The Review of Asset Pricing Studies

The Cross-Section of Cryptocurrency Returns

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At a given point in time, bitcoin prices are different on exchanges located in different countries, or against different currencies. While existing literature attributes the largest price differences to frictions, like market segmentation, trading platforms advertize how to execute trades based on this information. We provide a novel risk-based explanation of these price differences for a sample containing the most reputable exchanges and after accounting for all transaction costs and limitations to trade. Bitcoin prices for more expensive pairs are riskier because they depreciate more in bad times for cryptocurrency investors, when aggregate liquidity and investor sentiment are lower. (*JEL* G12, G14, G15, F31).

Received January 26, 2021; editorial decision December 1, 2021 by Editor Jeffrey Pontiff. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Investors buy bitcoins on a multitude of exchanges located in different countries and against different currencies. At one point in time, and in a frictionless world where investors could trade instantaneously across exchanges, the bitcoin price, converted in a common currency, should be the same everywhere and for any currency pair. Instead, large differences exist in bitcoin prices across exchanges located in different countries or for different currency pairs. Investors know these differences and discuss them extensively on cryptocurrency and investment social platforms.

Common explanations for these large and persistent price differences, or *bitcoin discounts*, are limits to arbitrage and market inefficiency (Makarov and Schoar (2019)). According to these explanations, and because of the enormous arbitrage opportunities available, cryptocurrency markets are

We thank Bob Chirinko, Sergei Kovbasyuk, Gabriele Zinna, Paolo Santucci de Magistris, Aleh Tsyvinski, Yukun Liu, Paolo Porchia and seminar and conference participants at LUISS, EIEF, Crypto Valley Conference on Blockchain Technology, Technische Universitat Berlin, Bank of Italy, University of Navarra, ICEF (HSE), CFE-CFStatistics 2018, CFE-CFStatistics 2019. Aleksandr Schneider provided excellent research assistance. Some of the material in this paper previously circulated under the title "Cryptomarket Discounts". Send correspondence to Nicola Borri, nborri@luiss.it.

The Review of Asset Pricing Studies 12 (2022) 667–705

https://doi.org/10.1093/rapstu/raac007 Advance Access publication 7 March 2022

highly inefficient. While various frictions and the opacity of many exchanges can explain the largest differences in bitcoin prices, we document significantly smaller differences, but economically significant, also in a sample where these frictions are likely to be small, and for the most reputable exchanges. This casts doubts over the possibility that these stories alone could provide a comprehensive explanation. In this paper, after accounting for all the transaction costs, we show that these arbitrage-like opportunities are not riskless and then propose a novel explanation that relates deviations in bitcoin prices to aggregate risk in cryptocurrency markets. As cryptocurrency markets become more mature, limits to arbitrage stories are likely to play a lesser role. Instead, we show that the risk-based explanation of bitcoin discounts applies also to the more recent sample.

With the rapidly growing importance of bitcoin and blooming of dozens of new cryptocurrencies, it becomes crucial to study the efficiency and structure of cryptocurrency markets. We focus on bitcoin because it was the first cryptocurrency, and it currently accounts for two-thirds of the total market capitalization and one-third of the trading volume, and then extend our analysis to a larger set of cryptocurrencies.

We carefully select the sample of exchange-currency pairs to minimize the impact of various frictions, like market segmentation, data reliability and liquidity; then, we form portfolios to isolate the possible common components, and accommodate the large time variation in the number of exchanges and currencies pairs. We select exchanges based on several indicators of "quality", including ratings, web traffic data, and liquidity. For example, the exchanges in our sample are not among those singled out for "fake volume and/or noneconomic wash trading" in a widely circulated report by Bitwise, the creator of the first crypto index fund (Bitwise (2019)). Furthermore, we use the capital control index constructed by Fernández et al. (2016) to select exchange locations and currency pairs available to international investors and we drop illiquid pairs. While this strategy dramatically reduces the number of exchanges and pairs in our sample, it can address the issue of data quality and market segmentation. Our baseline sample runs from May 2015 to May 2021 and, thus, includes the two boom-bust cycles for cryptocurrencies of 2017 and 2020.

We take the perspective of investors that observe bitcoin discounts and form portfolios according to two investable strategies. The first, which we refer to as the *cross* strategy, is based on the persistence of discounts and is designed to buy bitcoin using a benchmark exchange-currency pair and to sell bitcoin using relatively "expensive" exchange-currency pairs. The second, which we refer to as the *within* strategy, is based on the mean-reversion of discounts and is designed to buy bitcoin using relatively "cheap" exchange-currency pairs and to sell bitcoin at a later date using the same pair.

The first portfolio contains the pairs with the smallest average discounts (i.e., the "cheapest" pairs), while the last portfolio the pairs with the largest average discounts (i.e., the more "expensive" pairs). For both strategies, we obtain a large, and significant, cross-section of excess returns before transaction costs. Specifically, for *cross* portfolios, the average excess return of a long/short strategy that goes long in the last portfolio and short in the first portfolio is equal to 181 basis point per day. Similarly, for *within* portfolios, the average excess return of the long/short strategy is equal to 127 basis points per day. Although these returns are extremely large, they are mostly absorbed by transaction costs, which significantly reduce average returns by approximately 50 basis points for each of the *cross* portfolios and by 90 basis points for each of the *within* portfolios. In fact, the *within* returns are not statistically significant after accounting for all the transaction costs and fees. In contrast, the *cross* returns after transaction costs are smaller but significantly larger than zero. Since the *within* portfolio returns are negative after transaction costs, we concentrate our attention on net returns for *cross* portfolios. These results highlight the importance of studying net returns and one of the contributions of this paper is to use detailed data on transaction costs to distinguish gross and net returns.

To account for transaction costs, we collect data on withdrawal, deposit, margins, and trading fees for all the exchanges in the sample, and on bid/ask spreads for a subset of 33 pairs for which we are able to collect reliable data. We document a large heterogeneity in bid/ask spreads across exchanges, currency pairs, and time. We further extend the sample of bid/ask spreads using the estimates from predictive regressions of bid/ask spreads on intraday price volatility and trading volume and, for robustness, using the methodologies proposed by Roll (1984) and Abdi and Ranaldo (2017).

The average net excess return of a long/short *cross* strategy that goes long in the last portfolio and short in the first portfolio is equal to 31 basis points per day for a daily (non-annualized) Sharpe ratio of 13%. As a reference, over the same period and frequency, the Sharpe ratio of bitcoin returns is equal to approximately 6%, and the Sharpe ratio of U.S. market excess returns is approximately equal to 4%. Bid/ask spreads are responsible for most of this reduction. To roughly estimate the contribution of the different transaction costs, we note that withdrawal and deposit fees are typically small and lump sum and the average trading fee is 15 basis points per trade. Investors pay these costs twice for the *within* strategy, but only once for the *cross* strategy. This is because in the *cross* strategy, one of the two trades always involves the benchmark pair, the dollar-to-bitcoin pair on the Kraken exchange, for which these costs are negligible, especially for larger investors. Bid/ask spreads bite particularly long/short strategies, as they require four trades to be completed. However, we find that the short leg of the strategy does not contribute much to the overall returns. Then, investors could reduce transaction costs by executing only the long leg.

Both strategies are risky because investors, in order to form portfolios by bitcoin discounts, must transfer balances across exchanges and, then, buy and sell bitcoin at different times. The latter assumption captures the uncertain waiting times required by the architecture of both the blockchain (i.e., the time required for the proof-of-work) and the exchanges (i.e., the number of confirmations from the blockchain required to settle the transfers of balances), which imply that *pure*, instantaneous, arbitrage strategies are not implementable. Investors in the *cross* and *within* strategies face risks due to delays, possibly related to the speed of order execution and the inability to trade on a particular exchange due to a temporary shut down, along with the high volatility and low liquidity of cryptocurrencies.

We estimate a two-factor model to identify the common factors that could explain this cross-section. The first factor, which we call as the Bitcoin factor, is the crypto counterpart of the dollar factor from the currency risk premiums literature (Lustig and Verdelhan (2011)). The second factor, which we call the bitcoin carry factor, or $Carry_{Btc}$, is the return spread between the last and first portfolios and is highly correlated with the second principal component of *cross* portfolio returns. We find that $Carry_{Btc}$ explains a large fraction of the cross-sectional variation in portfolio returns.

We show that these returns compensate investors for taking on more aggregate risk in cryptocurrency markets. Bitcoin prices for more "expensive" pairs depreciate more in bad times for cryptocurrency investors, when aggregate liquidity and investor sentiment about bitcoin are lower. The basic finance logic we use for any other asset can be applied to cryptocurrencies. If an asset offers low returns when investors' marginal utility is high, it is risky, and then investors require a compensation through a positive excess return. We identify bad times for investors by projecting $Carry_{Btc}$ on a large set of crypto and noncrypto factors. We find that $Carry_{Btc}$ is unrelated to noncrypto factors, but that a large fraction of its variation is significantly and positively related to bitcoin aggregate liquidity risks, which we proxy for with the innovations to the mean bid/ask spreads on all pairs and the aggregate Amihud (2002) illiquidity measure; to bitcoin sentiment, which we proxy for with changes in the Google Trend index for the query "bitcoin" and with bitcoin momentum. Formal tests show that $Carry_{Btc}$ is a relevant factor in the time series and the cross-section of portfolio returns both in sample and out of sample. For the latter, we split the bitcoin pairs in our sample into two nonoverlapping groups and show that the $Carry_{Btc}$ risk factor obtained from the first group is priced in the cross-section of portfolio returns of the second group.

We evaluate the robustness of our results along several dimensions. First, we consider all transaction costs, like trading and margin fees, and show that the cross-section of portfolio returns remains large and significant, but trade size can substantially reduce portfolio returns. Second, we show that the *cross* and *within* strategies are implementable by building factor-mimicking portfolios of the long/short portfolios using two methodologies. The first admits long-only positions on the available assets in order to address the concern that investors could not short some of the pairs in our sample. The second additionally admits a short position on the bitcoin-to-dollar pair on Kraken that was available to all investors throughout the sample. Third, we show that our results are robust to a slower, weekly, frequency of rebalancing to address the concern that a daily rebalancing could not be implementable because, for example, of the time required to execute a trade on a given exchange or the convertibility in fiat currencies and the transfer of balances across exchanges. Fourth, we find that our results hold in a more recent sample, since 2018 when crypto "came of age." Fifth, we show that our results extend to samples that include other crypto-to-crypto pairs, like ethereum-to-bitcoin, or only crypto-to-fiat pairs, like ethereum-to-euro, providing a broader view on this new asset class. Note that, while governments can use domestic legislation to restrict flows of fiat currencies across borders, they have few instruments to restrict flows of cryptocurrencies.

This paper contributes to the recent and growing literature on empirical asset pricing of cryptocurrencies.[1] One strand of the literature studies the risk-return characteristics of cryptocurrencies, typically considering returns before transaction costs. Liu and Tsyvinski (2021) find that only crypto-specific risk factors, like investors' attention and momentum, can explain the time-series risk-return relation for cryptocurrencies. Liu, Tsyvinski, and Wu (forthcoming) show that the cross-section of returns for a large set of cryptocurrencies is explained by three crypto-specific factors, unrelated to traditional risk factors. These factors are unrelated to $Carry_{Btc}$, which, thus, contains additional pricing information. A second strand of the literature studies the efficiency and pricing of cryptocurrencies. Makarov and Schoar (2019) use bitcoin price differences across exchange-currency pairs to study the efficiency of cryptocurrency markets. In a small sample of pairs characterized by small bid/ask spreads, they document large arbitrage opportunities across exchanges in different locations and explain them with capital controls and weak financial institutions. In a companion paper, we expand Makarov and Schoar's sample to include all the fiat and cryptocurrencies and decompose the variability in bitcoin prices in components associated with, in order of importance, time, location of the exchanges, and currency pair (Borri and Shakhnov (2018)). Krückeberg and Scholz (2020), instead, attribute these price differences to market inefficiencies and untapped arbitrage opportunities. This paper builds a bridge between these two strands of the literature: it accounts for all the transaction costs and limitations to trade, and provides a

1 Yermack (2013), Velde (2013), and Dwyer (2015) are excellent primers that describe the functioning of the blockchain and cryptocurrencies. Catalini and Gans (2016), Biais et al. (2019), Cong, He, and Li (2020), and Ma, Gans, and Tourky (2018) analyze from the perspective of economic theory how blockchain technology and cryptocurrencies will influence the rate and direction of innovation and the incentives and equilibria behind the "proof of work" protocols.

risk-based explanation of bitcoin price differences across exchanges, currency pairs, and time. This paper is also related to the large finance literature on market efficiency and anomalies as well as limits to arbitrage. Some papers argue that market inefficiencies can explain differences in the prices of homogenous assets, others attribute them to differences in risk. Examples of the former, are Lee, Shleifer, and Thaler (1991); Chen, Kan, and Miller (1993) for closed-end funds; Lamont and Thaler (2003) for tech stock carve-outs; Gagnon and Karolyi (2010) for cross-listed stocks, such as ADRs; Burnside (2011) for the forward premium; and Du, Tepper, and Verdelhan (2018) for the deviations from the covered interest parity. Examples of the latter are Cochrane (2002) for tech stock carve-outs; Krishnamurthy (2002) for on the run and off the run bonds; and Lustig and Verdelhan (2007) for the forward premium. Pontiff (1996) and Tuckman and Vila (1992) argue that idiosyncratic risks limit arbitrage opportunities. This paper is the first to propose a risk-based explanation for bitcoin price differences across liquid fiat-to-bitcoin pairs traded on exchanges located in countries with no capital controls.

1. Bitcoin Portfolios

To investigate how far a risk-based explanation can go in explaining bitcoin price differences in different markets and against different currencies, we take the perspective of investors who form portfolios according to two strategies based on the persistence or mean-reversion of bitcoin discounts. By forming portfolios, we accommodate the large time-variation in the number of exchanges and currencies pairs and isolate common factors. For both strategies, we obtain a large and significant cross-section of returns before transaction costs. In this section, we focus on a sample in which frictions are small, containing the most liquid pairs and exchanges located in countries with limited constraints for foreign investors and satisfying a set of constraints in terms of "quality." Section 3 accounts for execution risks, additional transaction costs, and different samples.

1.1 Building portfolios

1.1.1 Data. Investors can trade bitcoin and other cryptocurrencies in two types of exchanges. The first, referred to as crypto-to-crypto exchanges, are exchanges on which only cryptocurrency pairs are traded (i.e., bitcoin for ethereum), and where investors can deposit and withdraw only cryptocurrencies; the second, referred to as fiat-to-crypto exchanges, are instead exchanges where investors can trade fiat currencies for cryptocurrencies (i.e., U.S. dollar for bitcoin), and deposit and withdraw both fiat and cryptocurrencies. While the second type of exchanges is subject to country regulations, for example, U.S.-based fiat-to-crypto exchanges are registered as a money service business with the Financial Crimes Enforcement Network of the U.S. Department of Treasury, the first type of exchanges is mostly unregulated, a point that has recently raised concerns about their reliability (Bitwise (2019); Gandal et al. (2018)) and risk of price manipulation using pump-and-dump schemes (Li, Shin, and Wang (2020)).[2]

The two types of exchanges also differ in the number of currency pairs traded: while investors can trade many, often in the hundreds, crypto-to-crypto currency pairs on crypto-to-crypto exchanges, they can trade only a few, mostly fiat-to-crypto, currency pairs on fiat-to-crypto exchanges. The majority of transactions takes place on exchanges that function like standard equity markets where investors submit buy and sell orders that are cleared by a centralized order book. Instead, other exchanges offer order-matching services and match buyers' and sellers' orders when they overlap. Finally, note that all exchanges operate 24/7, including Saturdays, Sundays, and holidays, and use the UNIX time-stamp to track time and ensure the immediate comparability of market prices.

We start by collecting daily bitcoin price and volume data for all exchanges and currency pairs available on the CryptoCompare website (https://cryptocompare.com/), a leading source of cryptocurrency trading data. In our baseline analysis, we restrict our sample along several dimensions in order to focus on reliable exchanges and currency pairs that are likely to be available to foreign investors.

First, we only consider fiat-to-crypto pairs on fiat-to-crypto exchanges (e.g., the dollar-to-bitcoin pair on Coinbase, but not the ether-to-bitcoin pair on Coinbase), because of the lower reliability of crypto-to-crypto exchanges. In what follows, we treat each fiat-to-crypto currency pair on a given exchange as a different asset. For example, we treat the dollar-to-bitcoin pair on Coinbase and the dollar-to-bitcoin pair on Kraken differently. Similarly, the dollar-to-bitcoin and euro-to-bitcoin pairs, both on Coinbase, are also different assets.

Second, we consider only fiat-to-crypto exchanges that satisfy several indicators of "quality," including ratings and web traffic data produced by

Third, to focus on pairs likely available to foreign investors, we include in the sample only pairs that satisfy both of the two following criteria to minimize the role of restrictions to capital flows. The exchanges must be located in one of the following countries: Australia, Canada, Denmark, the Eurozone, Hong Kong, Israel, Japan, Poland, Switzerland, the U.K., and

[2] According to the report by Bitwise (2019), 95% of the volume in CoinMarketCap is fake and/or noneconomic in nature. While this claim has not been independently verified, it is reasonable to assume that exchanges have an incentive to appear at the top of the lists used by media organizations to attract listing fees from ICOs and altcoins. We note that all the exchanges described in the report as fabricating data are crypto-to-crypto exchanges and, thus, not in our sample of bitcoin-to-fiat pairs. Li, Shin, and Wang (2020) argue that pump-and-dump schemes occur mostly on crypto-to-crypto exchanges, last only few minutes, and that fiat-to-crypto exchanges, like Bittrex, banned them. In Section B.I of the Internet Appendix, we report various "quality" indicators, for each exchange in the baseline sample (see Table A3).

the U.S. The fiat currencies must be one of the following: Australian dollar, Canadian dollar, Danish krone, euro, Hong Kong dollar, Israeli shekel, Japanese yen, Polish zloty, Swiss franc, British pound, the U.S. dollar. We select this set of countries and currencies based on the tightness in capital controls with respect to the United States using the capital control index constructed by Fernández et al. (2016).

Fourth, we compute U.S. dollar prices for all fiat-to-bitcoin pairs using daily spot rates from WM/Reuters and available on Datastream. For this reason, we exclude nonbusiness days because of the unavailability of spot rates. Fifth, to focus on the most liquid pairs, we consider the following additional restrictions. We exclude pairs with less than 30 days of observations; pairs traded on peer-to-peer platforms, which typically have very low volume; pairs with an average daily bid/ask spread larger than 2%; and observations corresponding to the 5-day average of daily volume smaller than 10 bitcoins.

Our baseline sample runs from May 26, 2015, to May 25, 2021. The starting date of the sample depends on the availability of a minimum number of pairs to build portfolios and the possibility of shorting the dollar-to-bitcoin pair. Our raw sample contains 258 fiat-to-bitcoin pairs, while our baseline sample contains, at most, 68 pairs traded on 29 exchanges. Table 1 contains descriptive statistics of the baseline sample. The number of exchanges and currency pairs increases over time because pairs enter and exit the sample as new exchanges open and close, and new pairs are introduced. Specifically, we start with 11 pairs traded on 16 exchanges and end with 68 pairs traded on 29 exchanges. Over the sample, the daily median trading volume increased from US$250,000 to approximately US$7.5 million. This corroborates the view that cryptocurrency markets have become more mature: despite the large increase in the number of pairs, the median trading volume did not decline. In the same period, the bitcoin price increased from approximately US$430 to about US$38,000 in May 2021.

1.1.2 Bitcoin discounts. Investors can trade bitcoin in a set of $m = 1, \ldots, M$ markets (i.e., exchanges), using a set of $j = 1, \ldots, J$ currencies. $P^*_{m,j}$ denotes the units of currency $j = 1, \ldots, J$ required to buy one bitcoin in market m (e.g., euros for bitcoin on Bitfinex). We take the perspective of U.S. dollar-based investors trading bitcoin in these markets and currencies. S^j denotes the spot exchange rate expressed in units of currency j per U.S. dollar (e.g., euro per dollar). The U.S. dollar price of one bitcoin in market m and currency j is

$$P_{m,j} = \frac{P^*_{m,j}}{S^j} \tag{1}$$

If investors could trade instantaneously across exchanges and in the absence of frictions, according to the law of one price they should get the same

Table 1
Baseline sample

	Price (Kraken)	Daily volume (USD millions)	Daily volume (BTC)			Baseline		All fiat-to-crypto	
Year	USD per BTC	median	median	p10	p90	# exchanges	# pairs	# exchanges	# pairs
2015	431.31	0.25	589.98	2.09	15,998.13	11	16	26	41
2016	960.77	0.55	662.24	17.44	8,510.73	12	18	31	51
2017	1,4402.20	43.52	3,085.81	17.61	24,788.88	15	25	48	86
2018	3,691.90	3.60	951.13	28.29	14,266.37	21	39	81	149
2019	7,168.30	1.15	157.08	10.92	4,713.13	26	47	82	152
2020	28,959.20	5.44	251.92	10.13	8,404.77	29	68	82	152
2021	38,388.10	7.63	165.71	10.28	7,273.81	29	68	82	152

The table reports descriptive statistics for the baseline sample. For each of the years from 2015 to 2021 we report the bitcoin price in U.S. dollars on the Kraken exchange (the benchmark pair); the median daily volume in millions of U.S. dollars and in units of bitcoin; the number of available exchanges and pairs. For the volume expressed in bitcoins, we also report the 10th and 90th percentile values (respectively, p10 and p90). The last two columns report the total number of available exchanges and pairs in the sample containing all the fiat-to-crypto pairs after eliminating peer-to-peer and illiquid exchanges. Descriptive statistics are for the last available day of each year. For 2021, they are for the last day of the sample in May 25, 2021. Data are from the Cryptocompare website (https://cryptocompare.com/) and Thomson Reuters.

dollars per bitcoin in each market m and currency j. In fact, there exist large, persistent, and time-varying price differences across both markets and currencies, and over time (see, e.g., Makarov and Schoar (2019); Borri and Shakhnov (2018)).[3]

We write the price in market $m = 1$, the Kraken exchange, and currency $j = 1$, the U.S. dollar, as the numeraire. This choice is motivated by the fact that Kraken is one of the oldest exchanges, launched in September 2013, with large bitcoin trading volume and low transaction costs. In addition, Kraken is one of the first exchanges to introduce margin trading and the possibility of short-selling the dollar-to-bitcoin pair. At a given point in time, we define the bitcoin discount in market m and currency j as

$$D_{m,j} = \frac{P_{m,j}}{P_{1,1}} - 1. \tag{2}$$

If $D_{m,j} < 0$, then investors get a smaller number of dollars per bitcoin in market m and currency j than in the reference market. On the contrary, if $D_{m,j} > 0$, then investors get a larger number of dollars per bitcoin in market m and currency j than in the reference market. Finally, when $D_{m,j} = 0$, investors get the same number of bitcoins in market m and currency j as they get in the reference market.

Figure 1 summarizes some of the properties of the bitcoin discounts for the pairs in our sample. Specifically, the top panel plots the median discount (red mark), along with the 25th and 75th percentiles (blue box) and the bottom panel. The bottom panel reports the half-life for each pair, where the latter captures the time it takes for a shock to dissipate by 50% and is estimated using an autoregressive process of order 1 on discounts. Discounts are, on average, different from zero and usually positive and volatile. For the average pair, almost 17% of the daily observations have discounts larger than 1% in absolute value. Within the same market, discounts are time varying and can be positive and negative and can reach absolute values of 30%. Finally, discounts are persistent and mean-reverting with a mean (median) half-life of 0.98 (0.48) days. According to standard augmented Dickey-Fuller tests, we reject the null of unit root for all pairs at standard significance levels.

1.1.3 Bitcoin excess returns. We assume investors can borrow at the dollar risk-free rate R^f and use lowercase letters the log of any variable (i.e., $x = \log(X)$). We consider the following two strategies based on observed bitcoin discounts. The first is a *cross* strategy that exploits the persistence

[3] Given the current blockchain technology, a minimum 10-minute wait for confirmation in the bitcoin blockchain is hardcoded into the program, and exchanges typically require more than one confirmation before deposit cryptocurrencies in investor's accounts. Therefore, unless investors have the possibility to buy and short-sell bitcoin and keep balances in different exchanges, they cannot trade instantaneously across exchanges. However, short-selling is not possible in all exchanges and maintaining balances implies inventory costs. For these reasons, although higher-frequency (i.e., intraday) data are available, we do not use them in the construction of returns.

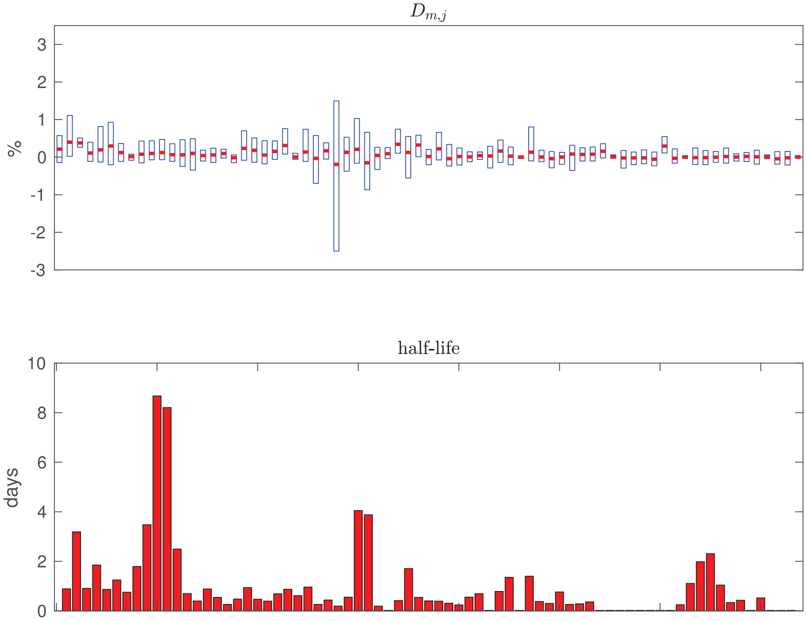

Figure 1
Bitcoin discounts
The top panel of the figure presents a boxplot of bitcoin discounts ($D_{m,j}$) for all the pairs in the baseline sample. For each box, the central red mark represents the median discount, and the bottom and top edges of the box represent the 25th and 75th percentiles. The bottom panel presents a bar plot where each bar corresponds to the half-life of one of the pairs in the baseline sample. To measure the half-life, we run an autoregressive process of order 1 on discounts: the half-life is equal to $\log(0.5)/\log(\rho)$, where ρ is the persistence parameter, and captures the time it takes for a shock to dissipate by 50%. Note that according to standard augmented Dickey-Fuller tests, we reject the null of unit root for all pairs at standard significance levels. Daily data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters for the period May 26, 2015, to May 25, 2021.

of bitcoin discounts. The second is a *within* strategy, based on the mean reversion of bitcoin discounts.

Figure 2 exemplifies the timing of the *cross* strategy using data for the bitcoin-to-euro pair on Bitfinex for May 8, 2019. At time t, an investor observes a discount $D_t = 4.22\%$ for the bitcoin-to-euro pair traded on Bitfinex. She then borrows one U.S. dollar at the risk-free rate to buy bitcoin using the benchmark bitcoin-to-dollar pair on Kraken. Note that, for the investor to complete the transaction, she first needs to deposit the initial dollar amount on the Kraken exchange (or she must have an existing balance). The investor then transfers her bitcoin balance to a different exchange, in the example Bitfinex. In Figure 2, the transfer, which could take up to 24 hours before confirmation, is represented by the vertical dashed line. At time $t + 1$, the investor first trades bitcoins for euros on Bitfinex and then exchanges euros for U.S. dollars on the foreign exchange market. Finally, the investor

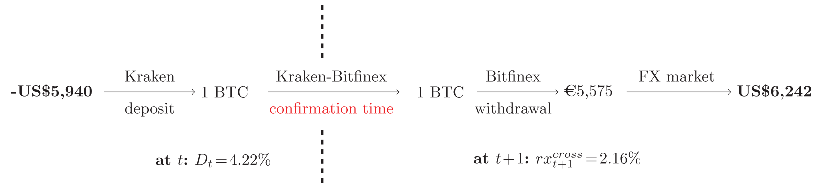

Figure 2
***Cross* strategy**
This figure exemplifies the timing of a *cross* strategy. At time t, the investor buys bitcoins with U.S. dollars in the reference market, that is Kraken, using the benchmark bitcoin-to-dollar pair. For the investor to complete the transaction, she first needs to deposit the initial dollar amount on the Kraken exchange (or she must have an existing balance). The investor then transfers her bitcoin balance to a different exchange (Bitfinex in the figure). The transfer could take up to 24 hours before confirmation. At time $t+1$, the investor first trades bitcoins for euros on Bitfinex, and then exchanges euros for U.S. dollars at the spot rate on the foreign exchange (FX) market. Because of the uncertainty around the confirmation time, we make the conservative assumption of a period to be equal to 1 day. The figure is based on data for t equal to May 8, 2019, when the discount associated with the bitcoin-to-euro pair on Bitfinex was equal to 4.22%. The resultant daily *cross* return was equal to 2.16%.

pays back the initial loan plus any accrued interest. The daily return of the *cross* trade in this example is equal to 2.16%.

Cross excess returns, expressed in U.S. dollars, are then

$$\begin{aligned} rx^{cross}_{m,j,t+1} &= p_{m,j,t+1} - p_{1,1,t} - r^f_t, \\ &= p^*_{m,j,t+1} - s^j_{t+1} - p^*_{1,1,t} - r^f_t, \end{aligned} \tag{3}$$

where $p_{m,j}$ and $p^*_{m,j}$ are, respectively, the (log) prices of pair j in market m expressed in dollars and units of currency j, and s^j is the (log) spot exchange rate in units of currency j per dollar (see Equation 1). Note that, for the *cross* strategy, the transaction at time t always occurs using the benchmark dollar-to-bitcoin pair on Kraken. Despite some similarities with an arbitrage strategy, this is actually a risky trade. In fact, investors are exposed to the risk of price changes during the transfer of bitcoins from Kraken at time t to market m at time $t+1$ (in the figure Coinbase). In addition, investors are further exposed to the exchange rate risk at $t+1$, with the exception of trades against other dollar-to-bitcoin pairs.

Because of the uncertainty around the confirmation time, we make the assumption of a period to be 1 day and we show that results are robust to a slower weekly frequency. The exchange Kraken advertises an average confirmation time of 1 hour. However, according to data we collect from the data provider https://www.blockchain.com, the confirmation time varies over time: the 99th percentile of the average confirmation time for a given day is approximately equal to 24 hours, and the average is equal to one hour.

The *within* strategy is a standard buy-and-hold investment for a particular pair j traded on a given exchange m with a holding period of one day. *Within* excess returns, expressed in U.S. dollars, are then

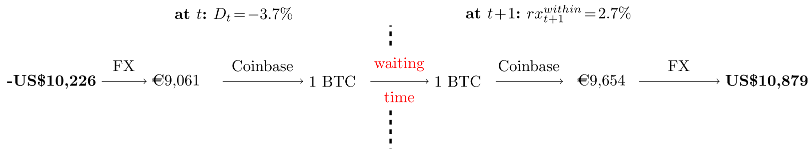

Figure 3
***Within* strategy**
This figure exemplifies the timing of a *within* strategy. At time t, the investor buys bitcoins with U.S. dollars using the bitcoin-to-euro pair on Coinbase. For the investor to complete the transaction, she first needs to deposit the initial dollar amount on the Coinbase exchange (or she must have an existing balance). At time $t+1$, the investor first trades bitcoins for euros on Coinbase, and then exchanges euros for U.S. dollars at the spot rate on the foreign exchange (FX) market. Because of the uncertainty around the execution time, we make the conservative assumption of a period to be equal to 1 day. The figure is based on data for t equal to July 14, 2019, when the discount associated with the bitcoin-to-euro pair on Coinbase was equal to −3.77%. The resultant daily *within* return was equal to 2.7%.

$$\begin{aligned} rx^{within}_{m,j,t+1} &= p_{m,j,t+1} - p_{m,j,t} - r^f_t, \\ &= p^*_{m,j,t+1} - p^*_{m,j,t} - \Delta s^j_{t+1} - r^f_t. \end{aligned} \tag{4}$$

Figure 3 exemplifies the *within* strategy using data for the bitcoin-to-euro pair on Coinbase for July 14, 2019. At time t, an investor observes a discount $D_t = -3.7\%$ for the bitcoin-to-euro pair traded on Coinbase. She then borrows one U.S. dollar at the risk-free rate, exchanges it to euros on the foreign exchange market to buy bitcoin using the bitcoin-to-euro pair on Coinbase. At time $t+1$, the investor first trades bitcoins for euros on Coinbase, and then exchanges euros for U.S. dollars on the foreign exchange market. The daily return of the *within* trade in this exaple is equal to 2.7%.

In the construction of returns for both strategies, we need to account for the possibility of exchange shutdowns: that is the fact that investors cannot complete their desired trade at $t+1$ because of the nonavailability of a given fiat-to-bitcoin pair. Temporary shutdowns are relatively frequent, for example, because of distributed denial-of-service attacks (DDos) or software malfunction. We make the assumption that investors, in case of a shutdown, can sell their bitcoins at the median price prevailing at $t+1$ across all pairs. In Section 3 we consider additional execution risks and evaluate the robustness of our assumption.

1.1.4 Bid and ask prices. We obtain daily bid-ask spreads data from Bitcoinity for a subset of 33 fiat-to-bitcoin pairs in our sample. In addition, we estimate bid and ask prices for all the remaining fiat-to-bitcoin pairs using the predicted values from the following panel regression:

$$BA_{m,j,t} = \alpha_j + \gamma_t + B(L)v_{m,j,t} + A(L)hl_{m,j,t} + \epsilon_{m,j,t}, \tag{5}$$

where $B(L)$ and $A(L)$ are fifth-order lag polynomial, v is the log trading volume in bitcoins, hl is the lag of the high-low spread, and α_j and γ_t are currency and time fixed effects.[4] Returns net of bid-ask spreads are

$$r^{cross,net}_{m,j,t+1} \equiv p^{ask}_{m,j,t+1} - p^{bid}_{1,1,t} = p_{m,j,t+1} - 0.5BA_{m,j,t+1} - (p_{1,1,t} + 0.5BA_{1,1,t}), \tag{6}$$

$$r^{within,net}_{m,j,t+1} \equiv p^{ask}_{m,j,t+1} - p^{bid}_{m,j,t} = p_{m,j,t+1} - 0.5BA_{m,j,t+1} - (p_{m,j,t} + 0.5BA_{m,j,t}), \tag{7}$$

where $BA_{m,j} = (p^{ask}_{m,j} - p^{bid}_{m,j})/p^{ask}_{m,j}$ is the bid-ask spread for market m and currency j, and we assume that the price without transaction costs is halfway between the bid and ask prices.

1.1.5 Portfolios. At the end of each day t, investors form two sets of seven portfolios sorted by bitcoin discounts $D_{m,j,t}$. Portfolios are ranked from the lowest negative to the highest positive bitcoin discount. For the first set of portfolios, investors use the *cross* strategy. For the second set of portfolios, investors use the *within* strategy. These strategies are implementable, in the sense that they are based on signals available to all investors. To execute a *cross* strategy investors must transfer crypto and fiat currencies across exchanges. The *within* strategy, on the other hand, requires transfers of cryptocurrencies only to adjust balances. In fact, we note that the *cross* strategy is popular among cryptocurrency investors, and websites like https://bitsgap.com/arbitrage-tool/ or https://arbismart.com/ offer the possibility to identify in real-time the largest discounts and immediately start *cross* trades.

In the *cross* strategy, investors always start at time t by buying bitcoin using the benchmark pair. Recall that negative (positive) discounts refer to pairs that have a low (high) price relative to the benchmark. Portfolio 1, then, groups the returns from selling, at time $t+1$, the pairs with the lowest discounts at time t (i.e., the "cheapest" pairs), while portfolio 7 groups the pairs with the highest discounts at time t (i.e., the more "expensive" pairs). In the *within* strategy, investors buy and hold one pair for 1 day. Portfolio 1, then, groups the returns from investing in the pairs with the lowest discounts, while portfolio 7 in the pairs with the highest discounts.

[4] The (within)-R^2 of our panel estimation is 20%, and most of the coefficients are significant at standard confidence levels. Specifically, higher trading volume and lower high-low spread are associated with smaller bid/ask spreads. Brauneis et al. (2021) argue that low frequency liquidity measures, for example based on high and low prices, are good estimates of actual liquidity measured with high-frequency indicators. Section B.II of the Internet Appendix presents estimates of bid/ask spreads using alternative estimators based on daily high, low, and close prices. Note that while the bid-ask spreads for the most liquid pairs in our sample are small and consistent with other studies (Dyhrberg et al., 2018), those for the less liquid pairs are an order of magnitude larger. Finally, some exchanges do not offer a limit order book, but only a matching of buy/sell orders. For these exchanges our bid/ask estimates are a proxy of liquidity, as they do not explicitly post bid/ask prices.

For both sets of portfolios, we compute the bitcoin excess returns $rx_{k,t+1}$ for portfolio k by taking the average of the bitcoin excess returns in each portfolio k:

$$rx_{k,t+1} = \frac{1}{N_k} \sum_{\{m,j\} \in P_k} rx_{m,j,t+1}.$$

The total number of pairs in our portfolios varies over time. We have a total of 11 assets at the beginning of the sample in May 2015, and 64 at the end of the sample in May 2021. The maximum number of pairs attained during the sample is 64. Note that we start building portfolios in May 2015 because of the availability of a minimum number of pairs and the possibility of shorting bitcoin on Kraken, our benchmark exchange.

1.2 Returns to bitcoin speculation for a U.S. investor

Table 2 offers a quick snapshot of the properties of the two sets of seven portfolios sorted by bitcoin discounts. For each portfolio k, we report the average and standard deviation of discounts (panel A); *cross* returns (panel B); and *within* returns (panel C). For returns, we also report the average of long/short returns. For *cross* returns, the long/short returns correspond to a high-minus-low strategy that goes long in portfolio 7 and short in portfolio 1 (i.e., $7-1$). For *within* returns, the long/short returns correspond to a low-minus-high strategy that goes long in portfolio 1 and short in portfolio 7 (i.e., $1-7$). For returns, we also report standard errors, computed by bootstrap, and Sharpe ratios computed as the ratio of mean to standard deviation of daily excess returns. All moments are daily, and Sharpe ratios are not annualized.[5]

Panel A reports the average bitcoin discounts. Portfolio 1 contains pairs with the largest negative discounts and portfolio 7 pairs with the largest positive discounts. Recall that when discounts are negative (positive), investors get a smaller (larger) number of dollars per bitcoin than they would in the case of the benchmark pair on Kraken. Across the seven portfolios, discounts increase monotonically from -97 basis points to 152 basis points *per day*.

Panel B shows that, by sorting pairs by their discounts, we obtain a monotonic increasing cross-section of gross and net *cross* returns. Specifically, gross excess returns increase, across the seven portfolios, from 14 basis points to 153 basis points *per day*. Standard deviations of excess returns are similar across portfolios so that we also obtain a cross-section of Sharpe ratios. Specifically, daily Sharpe ratios increase from 3% to 32%. The standard errors indicate that for all portfolios average returns are significantly different

[5] In Section F.VIII and F.II of the Internet Appendix, we show that the properties of the bitcoin portfolios are robust to smaller and larger numbers of portfolios and provide evidence of no clustering of subsets of the pairs in any portfolio using the k-means clustering test.

Table 2
Bitcoin portfolios: U.S. investor

Portfolio	1	2	3	4	5	6	7	Long/short
				A. *Discounts*				
Mean	−0.97	−0.28	−0.08	0.08	0.26	0.51	1.52	
SD	1.41	0.66	0.59	0.62	0.73	0.94	1.82	
				B. Cross *returns*				**7-1**
				Gross returns				
Mean	0.14	0.39	0.45	0.55	0.66	0.86	1.53	1.39
SD	4.67	4.58	4.62	4.64	4.66	4.64	4.77	2.22
SE	0.12	0.12	0.12	0.12	0.11	0.12	0.11	0.06
SR	0.03	0.09	0.10	0.12	0.14	0.19	0.32	0.62
				Returns net of bid/ask				
Mean	−0.23	0.16	0.26	0.35	0.46	0.62	1.10	0.58
SD	4.69	4.58	4.62	4.67	4.66	4.65	4.79	2.29
SE	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.06
SR	−0.05	0.03	0.06	0.08	0.10	0.13	0.23	0.25
				C. Within *returns*				**1-7**
				Gross returns				
Mean	1.15	0.68	0.53	0.47	0.40	0.35	0.03	1.12
SD	4.92	4.64	4.66	4.65	4.65	4.59	4.49	2.14
SE	0.13	0.12	0.12	0.12	0.12	0.12	0.11	0.06
SR	0.23	0.15	0.11	0.10	0.09	0.08	0.01	0.52
				Returns net of bid/ask				
Mean	0.47	0.27	0.22	0.14	0.07	−0.07	−0.77	−0.37
SD	4.89	4.65	4.67	4.69	4.65	4.62	4.63	2.19
SE	0.13	0.11	0.12	0.13	0.12	0.12	0.12	0.05
SR	0.10	0.06	0.05	0.03	0.01	−0.01	−0.17	−0.17

This table reports, for each portfolio $k = 1, \ldots, 7$, the mean, and standard deviation for the average discounts (panel A); the mean (*Mean*), standard deviation (*Std*), standard error (*SE*), and Sharpe ratio (*SR*) for the *cross* returns (panel B) and for the *within* returns (panel C). Standard errors are by bootstrap, and Sharpe ratios are computed as ratios of daily means to daily standard deviations and are not annualized. Only for returns, the table reports the mean, standard deviation, standard error, and Sharpe ratio for long/short excess returns, defined as the returns of a zero-cost strategy that goes long in portfolio 7 and short in portfolio 1 for *cross* returns; and long in portfolio 1 and short in portfolio 7 for *within* returns. For both the *cross* and *within* investment strategies, we consider both gross and net returns. Portfolios are constructed by sorting assets into seven groups at time t by their discounts $D_{m,j,t}$. The first portfolio contains the pairs with the lowest negative discounts. The last portfolio contains the pairs with the highest positive discounts. Data are from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters. The sample period is May 26, 2015, to May 25, 2021.

from zero as they are more than two standard errors from zero.[6] A zero-cost high-minus-low strategy that goes long in portfolio 7 and short in portfolio 1 produces large and statistically significant excess returns of approximately 139 basis points.

For many pairs, bid/ask spreads are not negligible. In fact, net returns are 37 basis points smaller for the first portfolio, and almost 43 basis points smaller for the last portfolio. The average return of the long/short strategy is substantially smaller after accounting for transaction costs and approximately equal to 59 basis points for a Sharpe ratio of 26%. Net long/short

[6] We reject the null of equal returns, at standard significance levels, for the corner portfolios using Newey and West (1986) heteroscedasticity and autocorrelation consistent standard errors. In addition, we also find that the Patton and Timmermann (2010) tests for a monotonic relationship (MR and MR^{all}) reject the null of flat or weakly decreasing pattern against the alternative of strictly increasing pattern.

returns are not simply equal to the difference between the corner portfolios' net returns. As back of the envelope calculation, consider that long/short net returns are instead equal to the long/short gross returns net of the difference between the averages of the gross and net returns of the corner portfolios (i.e., $1.39-(1.53-1.10)-(0.14+0.23)=0.59$). To go short in portfolio 1, investors must be able to short bitcoin on Kraken, our benchmark exchange. Kraken introduced margin trading and the possibility to open short positions starting on May 5, 2015, thus at the beginning of our sample. At the time of this writing, several of the exchanges in our sample offer margin trading, but in 2015, investors could short bitcoin only on Kraken and Bitfinex.[7] In Section 3, we will show that the mean long/short return remains positive and statistically different from zero also after accounting for exchange and margin fees.

Panel C of Table 2 shows that, by sorting pairs by their discounts, we also obtain a monotonic decreasing cross-section of gross and net *within* returns. Specifically, gross returns decrease, across the seven portfolios, from 115 basis points to 3 basis points *per day*. However, net returns are negative or not statistically different from zero for all portfolios, except for the first and the second. In fact, while the gross long/short average return is equal to 112 basis points per day, the corresponding average net return is equal to -37 basis points per day. Therefore, the *within* strategy is not economically profitable. Further, in order to implement the long/short *within* strategy over time, investors need to be able not only to transfer either bitcoin or fiat currency across exchanges but to short pairs on all exchanges. The latter is not always possible. Alternatively, for the short position, investors could keep balances of fiat currencies on all exchanges; for the long position, investors could keep balances of bitcoin on all exchanges. These balances would grow over time, exposing investors to inventory costs related to changes in bitcoin and fiat currency prices.

For both the *cross* and *within* long/short strategies, the long position accounts for most of the return, while the contribution of the short position is negligible. This is important for two reasons. First, as discussed above, short positions are not available on all exchanges or for the entire sample. Second, the short position accounts for one-half of the transaction costs and, additionally, requires the payment of margin fees (see also Table 7). Therefore, we consider the net returns from the long/short strategies as conservative estimates of the returns available to investors. Although the daily Sharpe ratios associated with the *cross* and *within* long/short strategies are large, in Section 3 we highlight that the Sharpe ratio associated with a realistic portfolio, with a relatively small fraction invested in the crypto asset and the

[7] Alternatively, investors could hold balances on all exchanges. Specifically, for the short position, investors could keep balances of fiat on all exchanges and bitcoin on Kraken. At the end of each period, investors should adjust their balances by transferring bitcoin to Kraken.

rest in the U.S. equity market, is only marginally higher than the market Sharpe ratio. In the Internet Appendix, we further show that our results are robust with respect to several extensions: Section F.IV considers a larger sample that includes nonbusiness days; Section F.V considers the average returns of factor-mimicking portfolios of the long/short *cross* and *within* strategies that are likely to be available to investors; and Section F.VI presents the results for a slower weekly frequency of rebalancing.

2. Common Factors in Bitcoin Returns

We have uncovered two different cross-sections of bitcoin excess returns related to strategies based on observed bitcoin discounts. After accounting for transaction costs, portfolio *within* returns are not statistically different from zero. These returns, then, are likely evidence of frictions that prevent investors from absorbing price differences across markets and pairs. In contrast, we have found a significant cross-section of portfolio *cross* returns after accounting for transaction costs. The latter is a popular strategy among investors and facilitated by trading platforms that advertize bitcoin discounts.

In this section, we show that the large cross-section of *cross* portfolio returns captures the compensation that investors demand to bear aggregate risk in cryptocurrency markets. Differences in portfolio *cross* returns are matched by covariances with just two risk factors: the bitcoin return on Kraken (Btc_{Kraken}), and the excess return form a long/short zero-cost strategy that goes long in the last portfolio and short in the first (i.e., $7-1$). We refer to this second factor as $Carry_{Btc}$. The first factor is a *level* factor that captures the returns of investing in bitcoin using the benchmark pair, that is the dollar-to-bitcoin pair on Kraken, and is the crypto counterpart of the Dollar factor in the currency risk premium literature (Lustig and Verdelhan (2011)). The second is a *slope* factor that explains the cross-section of portfolio returns. We show that $Carry_{Btc}$ is related to bitcoin aggregate liquidity and sentiment, while it is not related to traditional risk factors, like the Fama and French (1993) factors for equity markets. Note that in this section we always consider portfolio returns net of bid/ask spreads, and not gross returns. In Section 3 we additionally account for exchange trading and margin fees.

2.1 Results

We construct a two-factor model. The first factor, denoted by Btc_{Kraken}, is simply the return of an investment in the bitcoin-to-dollar pair on Kraken, our benchmark pair. The second factor, denoted by $Carry_{Btc}$, captures the excess returns of a zero-cost strategy that goes long in portfolio 7 and short in portfolio 1. These factors are highly correlated with the first two principal components of portfolio returns.

Table 3
Descriptive statistics: Risk factors

	Mean	*SD*	*Skew*	*Kurt*	$VaR_{1\%}$	$Corr(PC_1, x)$	$Corr(PC_2, x)$
$Carry_{Btc}$	0.59	2.30	−1.14	46.92	−4.03	0.07	0.87
Btc_{Kraken}	0.35	4.63	−0.07	9.75	−12.81	0.99	−0.03
Cross	0.42	4.53	−0.03	10.41	−12.60	1.00	−0.00

The table reports mean (*Mean*), standard deviation (*SD*), skewness (*Skew*), kurtosis (*Kurt*), value at risk with confidence 1% ($VaR_{1\%}$), and correlation coefficients with respect to the first two principal components for $Carry_{Btc}$, Btc_{Kraken}, and *Cross* ($Corr(PC_i, x)$, with $i = 1, 2$ and $x = Carry, Btc, Cross$). $Carry_{Btc}$ denotes the excess returns of a zero-cost *cross* strategy that goes long in portfolio 7 and short in portfolio 1. Btc_{Kraken} denotes the returns of investing in bitcoins using the benchmark dollar-to-bitcoin pair on the Kraken exchange. *Cross* denotes the returns for an investor that goes long in all the *cross* portfolios. All returns are net of bid/ask spreads. Daily data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters for the period May 26, 2015, to May 26, 2021.

Table 3 presents descriptive statistics for these two risk factors, as well as a third factor, denoted by *Cross*, which is the average excess returns across all seven *cross* portfolios. The average return on $Carry_{Btc}$ is equal to 0.59% per day. $Carry_{Btc}$ returns are also volatile (2.30%), negatively skewed (−1.14), and have a very large kurtosis (46.92). The mean return on Btc_{Kraken} is approximately one-half the mean return on $Carry_{Btc}$, with a larger standard deviation. Therefore, while the Sharpe ratio of $Carry_{Btc}$ is approximately equal to 26%, the Sharpe ratio of Btc_{Kraken} is approximately 9%. $Carry_{Btc}$ is highly correlated with the second principal component (0.87) extracted from portfolio returns, while Btc_{Kraken} is highly correlated with the first principal component (0.99). Note how *Cross* is *de facto* the first principal component, and therefore is highly correlated with Btc_{Kraken}.

Table 4 reports the asset pricing results obtained using two procedures applied to the portfolios sorted on bitcoin discounts: a generalized method of moments estimation (GMM) applied to linear factor models, following Hansen (1982), and a two-state OLS estimation following Fama and MacBeth (1973), henceforth FMB (see Section E in the Internet Appendix for details on the estimation procedures).

2.1.1 Cross-sectional regressions. The top panel of the table reports estimates of the market prices of risk λ and the stochastic discount factor (SDF) loadings b, the adjusted R^2, root-mean-square error (RMSE), and the p-value of a χ^2 test for the null that all the cross-sectional prices errors are zero (in percentage points). The first risk factor, Btc_{Kraken}, has an estimated risk price of 13 basis points (GMM_2), compared with a sample mean of 32 basis points. All portfolios have a beta close to one with respect to this first factor. As a result, the first factor explains none of the cross-sectional variation in portfolio returns. This is why the standard errors on the risk price estimates are large. For example, the GMM standard error is 15 basis points. While the Btc_{Kraken} factor does not explain any of the cross-sectional variation in

Table 4
Asset pricing: U.S. investor

A. *Risk prices*

	$\lambda_{Btc_{Kraken}}$	$\lambda_{Carry_{Btc}}$	$b_{Btc_{Kraken}}$	$b_{Carry_{Btc}}$	R^2	$RMSE$	$\chi^2(\%)$
GMM_1	0.29	1.51	0.87	28.84	94.07	0.08	
	[0.17]	[0.28]	[0.77]	[5.43]			0.05
GMM_2	0.13	1.68	0.05	32.05	98.80	0.18	
	[0.15]	[0.21]	[0.69]	[4.06]			0.12
FMB	0.29	1.51	0.86	28.83	92.58	0.08	
	[0.12]	[0.07]	[0.56]	[1.26]			0.00
Mean	0.32	0.59					
s.e.	[0.12]	[0.16]					

B. *Factor betas*

Portfolio	α_0^k	$\beta^k_{Btc_{Kraken}}$	$\beta^k_{Carry_{Btc}}$	R^2	$\chi^2(\alpha)$	p-value (%)
1	−0.31	0.95	−0.39	92.39		
	[0.05]	[0.01]	[0.07]			
2	−0.15	0.96	−0.01	95.89		
	[0.03]	[0.01]	[0.02]			
3	−0.05	0.97	−0.01	96.80		
	[0.03]	[0.01]	[0.02]			
4	−0.04	0.97	0.13	95.45		
	[0.07]	[0.01]	[0.09]			
5	0.09	0.98	0.10	96.93		
	[0.03]	[0.01]	[0.04]			
6	0.21	0.97	0.18	95.47		
	[0.04]	[0.01]	[0.05]			
7	0.50	0.96	0.49	94.05		
	[0.07]	[0.01]	[0.09]			
All					614.49	0.00

Panel A reports results from GMM and Fama and MacBeth (1973) asset pricing procedures on the seven bitcoin portfolios sorted with respect to bitcoin discounts. Market prices of risk λ, the adjusted R^2, the root-mean-square error (*RMSE*), and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. All excess returns are multiplied by 100. Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel B reports OLS estimates of the factor betas. R^2s and p-values are reported in percentage points. The standard errors in brackets are Newey and West (1986) standard errors computed with the optimal number of lags according to Andrews (1991). The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey and West (1986) variance-covariance matrix (one lag) for the system of equations (see Cochrane (2009)). Daily data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters. The sample period is May 26, 2015, to May 26, 2021.

expected returns, it is important for the level of the average returns. The market price of risk of the second factor, $Carry_{Btc}$, is equal to 168 basis points *per day*. This means that an asset with a beta of one on the $Carry_{Btc}$, and a beta of zero on the first factor, earns a risk premium of 1.68% per day. The GMM standard error of the risk price is 21 basis points. The FMB standard error is only 7 basis points. So, the risk price is more than two standard errors from zero, and highly statistically significant.

Although pricing errors are small (the *RMSE* is just 18 basis points) and the adjusted R^2 is approximately 98%, we cannot reject the null that all pricing errors are zero, as $p-$values are around 12%. In Section F of the Internet Appendix, we show that $Carry_{Btc}$ is a priced risk factor also in portfolios at weekly frequency, and in a shorter sample starting in January 2018, after the bitcoin frenzy of 2017. In addition, we show that the market price of $Carry_{Btc}$ risk is time varying, and in particular, it is higher in bad times for financial markets, when the VIX volatility index is high.

2.1.2 Time Series Regressions. The bottom panel of Table 4 reports the intercepts (denoted by α^j) and the slope coefficients (denoted by β^j) obtained by running time-series regressions of each portfolio's excess returns Rx^k on a constant and the Btc_{Kraken} and $Carry_{Btc}$ factors. The first column reports α's estimates in percentage points *per day*. The point estimates are small but statistically different from zero, particularly in the corner portfolios. As a result, the null that the αs are jointly zero is rejected at standard significance levels. This indicates that the true factor structure possibly contains more than two factors. In fact, a principal component analysis (see Table A7 in the Internet Appendix) indicates that the third component, which captures curvature, has a contribution to the total variance similar to that of the second component and could contribute to explain differences in the expected returns of corner and middle portfolios. We do not include this additional risk factor due to the small number of portfolios. Further, the αs might capture the effect of possible frictions that we were not able to eliminate despite the restrictions on the sample and the use of portfolios. The second and third columns of the same panel report the estimated βs for the Btc_{Kraken} and $Carry_{Btc}$ factors. The βs on the Btc_{Kraken} factor are similar across portfolios and close to one, while the βs on the $Carry_{Btc}$ factor increase from -0.39 for the first portfolio to 0.49 for the last portfolio (i.e., portfolio 7).

A natural interpretation of our results is that portfolios with higher comovement with $Carry_{Btc}$ are riskier exactly because, on average, have high returns in good times for cryptocurrency investors, when $Carry_{Btc}$ excess returns are large, and low returns in bad times, when $Carry_{Btc}$ excess returns are small. On the contrary, Btc_{Kraken} is a level factor that explains the average excess return but does not price the cross-section of returns. In the next paragraph, we show that $Carry_{Btc}$ return is lower in bad times for crypto investors, when bitcoin liquidity and sentiment are lower.

2.1.3 What risks. We investigate whether standard noncrypto factors can span the $Carry_{Btc}$ and Btc_{Kraken} factors, as well as the *Cross* factor. Specifically, Table 5 presents the results of contemporaneous linear regressions of the return of each factor on a large set of crypto and noncrypto factors. We report Newey and West (1986) standard errors in brackets.

Panel A groups the crypto factors that we choose among crypto specific factors and the crypto counterparts of the "currency zoo," that is risk factors that have been proposed to explain the cross-section of currency returns. Btc_{Kraken} and $Carry_{Btc}$ are the crypto counterparts of the Dollar and Carry

Table 5
Disconnect between crypto and noncrypto factors

	$Carry_{Btc}$	Btc_{Kraken}	$Cross$
α	2.92[a]	0.11	0.32[a]
	[0.298]	[0.510]	[0.090]
		A. *Crypto factors*	
Btc_{Kraken}	0.02	–	0.96[a]
	[0.020]		[0.010]
$Carry_{Btc}$	–	0.09	0.06[a]
		[0.083]	[0.022]
MOM_{Kraken}	0.63[a]	0.02	0.09[a]
	[0.123]	[0.200]	[0.029]
MOM_{Btc}	0.25[a]	–0.10	–0.02[a]
	[0.059]	[0.066]	[0.009]
Vol_{Btc}	0.87	5.47[a]	0.32
	[0.576]	[1.877]	[0.192]
Liquidity	–35.28[c]	3.45	5.58
	[19.624]	[4.255]	[5.101]
BidAsk	–0.84[c]	0.31	–0.35[b]
	[0.484]	[0.566]	[0.142]
$\Delta Goog$	0.01	–0.01	0.00
	[0.007]	[0.015]	[0.003]
DDoS	–0.11[a]	–0.01	–0.02[a]
	[0.017]	[0.029]	[0.005]
		B. *Noncrypto factors*	
MKT	–0.04	–0.28	0.04
	[0.125]	[0.334]	[0.039]
SMB	–0.01	0.29	–0.02
	[0.127]	[0.306]	[0.045]
HML	–0.12	0.14	0.02
	[0.111]	[0.267]	[0.041]
MOM	–0.07	0.01	–0.01
	[0.088]	[0.194]	[0.030]
$Carry_{FX}$	–0.00	–0.15	0.06
	[0.139]	[0.296]	[0.041]
Gold	–0.03	0.36[b]	–0.01
	[0.093]	[0.182]	[0.030]
ΔVix	–0.00	–0.05	0.00
	[0.014]	[0.052]	[0.005]
Adj. R^2 (%)	23.706	3.107	97.340
F(%)	0.000	1.174	0.000

This table presents the results of contemporaneous linear regressions of $Carry_{Btc}$, Btc_{Kraken}, and *Cross* returns on different noncrypto and crypto factors. $Carry_{Btc}$ is the excess return of a zero-cost strategy long in portfolio 7 and short in portfolio 1; *Cross* is the return of a strategy long in all *cross* pairs. Portfolios are sorted by bitcoin discounts. Btc_{Kraken} is the return of the dollar-to-bitcoin pair on Kraken. Panel A groups the crypto factors, and panel B the noncrypto factors. The crypto factors are: the bitcoin (Btc_{Kraken}), carry ($Carry_{Btc}$), and two momentum (MOM_{Kraken}, MOM_{Btc}) factors; the global FX volatility factor of Menkhoff et al. (2012a) for cryptos (Vol_{Btc}); the mean of Amihud (2002)'s illiquidity (*Liquidity*) and innovations to the bid/ask spread (*BidAsk*) across all pairs; the change in the Google Trend index for the query "bitcoin" ($\Delta Goog$); the fraction of inactive exchanges (*DDoS*). MOM_{Kraken} is the cumulated bitcoin return over the previous 30 days (up to period $t-2$); MOM_{Btc} is the return of a zero-cost strategy long (short) in a portfolio containing the pairs with the highest (lowest) *cross* return in the previous 30 days. The noncrypto factors are: the Fama and French (1993) three equity factors (*MKT*, *SMB*, *HML*); the Carhart (1997) equity momentum factor (*MOM*); the currency carry trade ($Carry_{FX}$) factor, proxied by the return of the Deutsche Bank G10 currency carry trade ETF; the log price changes for the Gold Bullion (*Gold*), and the CBOE VIX volatility index (ΔVix). The last row reports the p-values (in percentages) of an F-test on all coefficients equal to zero (excluding the constant). Daily data come from the Cryptocompare website (https://cryptocompare.com), Thomson Reuters, Bloomberg, Google, and the Kenneth French data library for the period May 26, 2015, to May 26, 2021.

factors for currencies (see Lustig, Roussanov, and Verdelhan (2011)). MOM_{Kraken} and MOM_{Btc} are two crypto momentum factors. MOM_{Kraken} is the cumulated return of the dollar-to-bitcoin pair on Kraken over the previous 30 days. To construct MOM_{Btc}, we first sort all pairs by the *cross* return in the previous 30 days and then consider the return of the zero-cost strategy long (short) the portfolio containing the pairs with the highest (lowest) past return. The latter is the crypto counterpart of the momentum factor for currencies proposed by Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The momentum factors can be interpreted in terms of investor sentiment or overreaction channel (see Liu and Tsyvinski (2021) for cryptocurrencies or Nicholas, Shleifer, and Vishny (1998) for equities). We further consider an increase in the Google Trend index for the query "bitcoin" on all geographical areas ($\Delta Goog$) as proxy for investor sentiment, as it is associated with a greater interest for bitcoin. Liu and Tsyvinski (2021) consider this factor a proxy for investors' attention. Furthermore, we consider several proxies for aggregate crypto liquidity: Vol_{Btc} contains the crypto counterpart of the innovations to the global FX volatility factor of Menkhoff et al. (2012a); *Liquidity* and *BidAsk* are, respectively, the mean of the Amihud (2002) illiquidity indicator and the innovations to the bid/ask spread across all pairs. Finally, we consider the fraction of daily inactive exchanges (*DDoS*) as a proxy for bitcoin counterparty risk.

Panel B groups the noncrypto factors. We consider the standard Fama and French (1993) three factors (MKT, SMB, HML) and the Carhart (1997) momentum factor (MOM) for equities. In addition, we also include a proxy for the currency carry trade ($Carry_{FX}$); the log price changes for the Gold Bullion (*Gold*); the CBOE VIX volatility index (ΔVix). MKT, SMB, HML, and MOM are risk factors commonly used to price various types of assets, like equities and bonds, and are from the Kenneth French's website. *Gold*, like other precious metals, is considered a store of value, and a popular narrative considers cryptocurrencies an alternative to these precious metals. Δ Vix captures movements in aggregate liquidity and investors' risk aversion. Data on gold prices and the VIX index are from Datastream. We proxy the currency carry trade factor with the return of the Deutsche Bank G10 currency carry trade ETF, whose prices we obtain from Bloomberg.

We summarize our results as follows. First, we find that $Carry_{Btc}$, as well as Btc_{Kraken}, is unrelated to noncrypto factors, a finding that echoes Liu and Tsyvinski (2021) results for aggregate bitcoin returns. Second, while it is difficult to relate Btc_{Kraken} returns to observable factors (excluding Vol_{Btc}), we find that a sizeable fraction of the time-series variation in $Carry_{Btc}$ returns can be explained by different crypto factors. Specifically, we find that $Carry_{Btc}$ is lower when momentum returns are lower; when bitcoin liquidity risk is higher (i.e., when the Amihud (2002) illiquidity measure and the innovations to the average bid/ask spread are higher). In addition, $Carry_{Btc}$ returns tend to be lower when the Google Trend index is lower, although this effect is estimated imprecisely. Further, $Carry_{Btc}$ returns tend to be lower when the fraction of inactive exchanges is larger. These results highlight the fact that $Carry_{Btc}$ returns are risky because they are high (low) in good (bad) times for bitcoin investors. Differently from what Menkhoff et al. (2012a) show for currencies, we find that $Carry_{Btc}$ returns are not significantly related to innovations in global volatility. Because it is difficult to disentangle volatility and liquidity effects, the latter result might be explained by the fact that the two liquidity factors already capture the effect of global volatility. The significant relation between $Carry_{Btc}$ return and the measure of counterparty risk (*DDoS*) is related to the technological evolution of the infrastructure of crypto exchanges and will probably diminish or disappear as a risk factor when the market is more mature. For $Carry_{Btc}$, the adjusted R^2 is approximately equal to 30%, in comparison to the adjusted R^2 for Btc_{Kraken} of 3.6%, and the intercept (α) is large and significantly different from zero at standard confidence levels. These results are robust with respect to a different window in the construction of the momentum factors. Finally, we confirm that *Cross* is fully explained by the bitcoin return.

Liu, Tsyvinski, and Wu (forthcoming) identify three crypto factors that price the cross-section of cryptocurrencies. The three factors are a cryptocurrency market factor (CMKT), a cryptocurrency size factor (CSMB), and a cryptocurrency momentum factor (CMOM) and are only available at weekly frequency.[8] They argue that the momentum effect is concentrated among the large coins and is consistent with recent theories of investors' overreaction; that the size effect is mainly concentrated among the smallest coins and is interpreted as an illiquidity premium; while the market factor is simply the bitcoin return. In Table A11 (Section F of the Internet Appendix), we show that $Carry_{Btc}$ is not spanned by either the cryptocurrency size factor (CSMB) or the cryptocurrency momentum factor (CMOM). Instead, we interpret $Carry_{Btc}$ as a proxy for good times in crypto currency markets. In particular, we show that $Carry_{Btc}$ return is higher at times of higher liquidity and investor sentiment.

3. Robustness

In this section, we consider several extensions. First, we report additional characteristics of the bitcoin portfolios. Second, we carefully consider all transaction costs, like trading, margin and exchange fees. Third, we discuss Sharpe ratios for realistic portfolios including crypto and non crypto assets. Fourth, we consider alternative samples with more pairs, like additional fiat and crypto currencies. Fourth, we consider execution risk, that is the risk that a transaction is not executed within the range of recent market prices

[8] We are grateful to Yukun Liu for sharing the data on the three factors, which are only available at weekly frequency. We interested readers to Liu, Tsyvinski, and Wu (forthcoming) for details about the construction of the three factors and their interpretation.

observed by investors. Sixth, we consider the properties of portfolios with a slower weekly rebalancing.

The main takeaway of this section is that $Carry_{Btc}$ returns remain large and significant after accounting for all transaction costs and in more recent samples, or samples containing additional fiat-to-bitcoin, crypto-to-bitcoin and crypto-to-fiat pairs, and in portfolios rebalanced weekly. However, execution risk and trade size could substantially reduce $Carry_{Btc}$ returns.

We further test the robustness of our results by considering an out-of-sample experiment using two randomly selected subsamples from our data. We use the $Carry_{Btc}$ factor extracted from one random subsample to successfully price the cross-section of portfolio returns obtained using the *second* random sample.

3.1 Additional characteristics

Table 6 presents additional characteristics of the bitcoin portfolios sorted by discounts. We find that corner portfolios, that is portfolios with the largest positive or negative discounts, are characterized, on average, by lower liquidity and higher counterparty risk.

A lower trading volume and higher bid/ask spreads and intraday volatility indicate lower liquidity; a smaller wallet size, larger fraction of inactive pairs, and a lower rating (measured by the exchange grade points assigned by CoinMarketCap), indicate higher counterparty risk. The wallet size of an exchange not only captures the supply of bitcoins (i.e., the number of bitcoins in circulation on a particular exchange) but also provides a measure of assets for an exchange, similar to deposits for a financial institution.

We consider as additional indicators of counterparty risk the mean fraction of inactive pairs and exchange rating for each portfolio. The fraction of inactive pairs is the average number of pairs not available at time $t+1$, but in which investors could have invest at time t. As a back-of-the-envelope calculation, consider that the average number of pairs per portfolio is equal to six. Therefore, when the fraction of inactive pairs for a given portfolio is equal to 1%, there is one inactive pair in that portfolio every 16 days $(1/(6 \times 1\%) \approx 16)$. the Cryptocompare website (https://cryptocompare.com) assigns a rating to different exchanges, summarized by the grade points, where a higher number corresponds to a more reliable exchange.

The high/low spread, defined as the difference between the high and low daily bitcoin prices as a fraction of their average, also indicates a higher risk for investors because of the higher intraday volatility. The average degree of capital controls, measured by the overall restriction index ka from Fernández et al. (2016), is an indicator of the frictions that might prevent investors to

Table 6
Bitcoin portfolios: additional characteristics

Portfolio	1	2	3	4	5	6	7
			Volume (btc thousands)				
Mean	3.49	5.19	5.31	4.84	4.45	4.18	2.90
SE	0.19	0.19	0.19	0.19	0.24	0.21	0.11
			Bid-ask spread (%)				
Mean	0.37	0.24	0.19	0.20	0.20	0.24	0.43
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01
			High-low spread (%)				
Mean	6.07	5.82	5.79	5.76	5.80	5.71	6.01
SE	0.15	0.13	0.18	0.13	0.15	0.13	0.14
			Wallet (btc thousands)				
Mean	98.25	111.49	110.94	111.90	99.10	94.91	94.67
SE	2.69	2.94	2.98	3.03	3.03	2.84	2.35
			Fraction of inactive pairs (%)				
Mean	0.86	0.13	0.16	0.13	0.20	0.15	0.50
SE	0.14	0.05	0.08	0.05	0.06	0.05	0.09
			Exchange grade points				
Mean	47.26	50.04	51.24	51.40	51.21	49.66	45.95
SE	0.24	0.21	0.19	0.18	0.19	0.21	0.16
			Capital control index				
Mean	0.12	0.10	0.09	0.10	0.10	0.12	0.14
SE	0.36	0.29	0.24	0.23	0.21	0.27	0.26
			Exchange rate growth (%)				
Mean	−0.05	−0.05	−0.03	−0.00	0.03	0.03	0.03
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01

This table reports additional characteristics of the seven portfolios sorted by bitcoin discounts. The additional characteristics are: trading volume (in thousands of bitcoins); bid/ask spread (in percentage); high/low spread (in percentage); wallet size (in thousands of bitcoins); fraction of inactive pairs (in percentage); exchange grade points; and capital control index and exchange rate growth ((in percentage)). At each point in time t, and for each portfolio k, we compute the equally weighted average for each characteristic. Each panel reports mean, standard deviation and standard error by bootstrap estimated over the sample May 26, 2015, to May 25, 2021. The high/low spread is the difference between the high and low daily bitcoin prices as a fraction of their average. Details on the definition of inactive pairs and wallet size are in Section 3. Daily data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters. The exchange grade points are from the Cryptocompare and are constant for each exchange throughout the sample (a higher number corresponds to a more reliable exchange). The capital control index is the overall restriction index ka from Fernández et al. (2016) (ka is equal to 0.125 for the United States in 2019; a higher number is associated to more restrictions). Exchange wallets are manually obtained from Walletexplorer. Note that the ka is available at annual frequency up to 2019. For the sample since 2019, we fix ka to the last available values.

execute their trades. With respect to both of these measures, we do not find significant differences across portfolios.[9]

Finally, we observe that by sorting pairs by their discounts we obtain an increasing cross-section of average exchange rate growth (i.e., the change in the value of fiat currencies with respect to the dollar). Note that the average exchange rate growth is negative and significant for portfolio 1 (i.e., a dollar depreciation), and positive and significant for portfolio 7 (i.e., a dollar appreciation). Although economically small, the effect of the change in the exchange rate further increases the risk of the long/short strategy. For

[9] As reference, ka is equal to 0.13 for the United States at the end of 2019, and the average value across the seven portfolios is equal to 0.11 (lower values correspond to looser capital control levels).

example, an investor long in portfolio 7, on average, exchanges fiat currency for dollars at a lower rate.

3.2 Transaction costs

We now show how the returns of the two investment strategies change after accounting for all transaction costs, that is bid/ask spreads and trading fees. To roughly estimate the impact of transaction costs, note that the mean daily bid/ask spread is 27 basis points (Table 6), and the average trading fee is 15 basis points per trade (Table A3 in Section B.I of the Internet Appendix). Investors pay these costs twice for the *within* strategy, but only once for the *cross* strategy. This is because the *cross* strategy always involves one of the two trades on the benchmark pair, the dollar-to-bitcoin pair on the Kraken exchange, for which these costs are negligible.

In what follows, we carefully consider the heterogeneity in bid/ask spreads across portfolios; the market depth; and all trading and margin fees that can potentially affect returns. We focus on both the *cross* and *within* strategies and only on the long/short returns. Recall that, for *cross* investors, the long/short strategy goes short in the first portfolio, with the most negative discount. On the contrary, for *within* investors, the long/short strategy goes short in the last portfolio, with the most positive discount. Bitcoin investors must additionally pay deposit and withdrawal fees to the exchanges; trading fees and margin fees when entering short positions.

Table 7 documents the impact of the different transaction costs on the long/short returns. The left side of the table refers to *cross* returns, while the right side refers to *within* returns. Panel A reports gross average portfolios returns, and panels B to E report average portfolio returns for different specifications of the transaction costs.

Panel B reports the average portfolio returns net of bid/ask spreads, where the bid/ask spreads are those for the subset of 33 pairs for which we were able to collect data on Bitcoinity. As highlighted in the discussion of Table 2, bid/ask spreads have a differential impact across portfolios. Specifically, average returns decrease more for corner portfolios. Panel C additionally accounts for trading fees, which uniformly lower returns by 37 basis points for *cross* portfolios and by 67 basis points for *within* portfolios. After accounting for bid/ask spreads, net returns of long/short *within* strategies are negative. For this reason, in what follows we focus on the impact of additional transaction costs and frictions only on *cross* portfolios.

To evaluate the likely impact of trading fees on the cross-section of portfolio returns, we manually collect current trading fees for all the exchanges in our sample. For all exchanges, except Kraken, we fix trading fees to 0.15%, which corresponds to the median taker trading fee. Taker fees are charged to investors who absorb liquidity with market orders, as opposed to maker fees, which are charged to investors who provide liquidity by placing limit orders.

Table 7
Bitcoin portfolios: Long/short returns

	Cross returns long/short: $rx^k_{t+1} - rx^1_{t+1}$						*Within* returns long/short: $rx^k_{t+1} - rx^7_{t+1}$					
Portfolio	2-1	3-1	4-1	5-1	6-1	7-1	1-7	2-7	3-7	4-7	5-7	6-7
						A. *Gross returns*						
Mean	0.25	0.30	0.40	0.51	0.72	1.39	1.12	0.65	0.50	0.44	0.37	0.32
SE	0.12	0.12	0.12	0.11	0.12	0.11	0.13	0.12	0.12	0.12	0.12	0.12
						B. *Net of bid-ask*						
Mean	−0.16	−0.07	0.02	0.12	0.29	0.90	0.26	0.04	−0.04	−0.12	−0.20	−0.32
SE	0.04	0.04	0.05	0.05	0.05	0.06	0.05	0.03	0.03	0.04	0.03	0.03
						C. *Trading fees & net of bid-ask*						
Mean	−0.53	−0.44	−0.35	−0.25	−0.08	0.53	−0.41	−0.63	−0.71	−0.79	−0.87	−0.99
SE	0.04	0.04	0.06	0.05	0.05	0.06	0.05	0.03	0.03	0.03	0.03	0.03
						D. *Net of trading fees & bid-ask (synthetic)*						
Mean	−0.73	−0.63	−0.53	−0.43	−0.27	0.21	−1.04	−1.24	−1.29	−1.36	−1.44	−1.57
SE	0.04	0.04	0.05	0.05	0.05	0.06	0.06	0.04	0.04	0.04	0.03	0.03
						E. *Net of trading fees & bid-ask (10 btc depth)*						
Mean	−1.98	−1.81	−1.74	−1.72	−1.69	−1.29	−3.67	−2.97	−2.88	−3.01	−3.24	−3.66
SE	0.07	0.07	0.08	0.06	0.07	0.07	0.06	0.04	0.04	0.04	0.03	0.03

This table reports the mean and standard errors for the returns on long/short *cross* and *within* portfolios. For *cross* portfolios, the long/short strategy goes long in portfolio $k = 2, \dots, 7$ and short in the first portfolio. For *within* portfolios, the long/short strategy goes long in portfolio $k = 1, \dots, 6$ and short in the last portfolio. Panel A corresponds to gross portfolio returns. Panel B to returns net of bid/ask spreads for the subsample of bitcoin-to-fiat pairs for which we obtained bid/ask spreads from https://data.bitcoinity.org. Panel C to returns that additionally account for trading fees. Panel D to returns net of *synthetic* bid/ask spreads and trading fees. The *synthetic* bid/ask spreads are generated for all the bitcoin-to-fiat pairs using the predicted values from panel regressions of the available bid/ask spreads on the historical market data. Panel E corresponds to returns net of trading fees and bid/ask spreads at the market depth of 10 bitcoins. Daily data come from the Cryptocompare website (https://cryptocompare.com), Bitcoinity, and Thomson Reuters for the period May 26, 2015, to May 25, 2021.

Therefore, we implicitly assume investors post their offers, which are, then, executed within the horizon of one day. For the exchanges in our sample, the conservative estimates for the median taker and maker fees are, respectively, 0.25% and 0.15%. These values are calculated based on maximum fees for investors, but exchanges typically employ an asymmetric pricing model with fee discounts in order to incentivize higher levels of trading activity. As for Kraken, we fix the trading fee to 0%, which corresponds to the current fee charged to investors with total orders larger than US$10 million in a month. Our choice is motivated by the fact that, for the *cross* strategy, investors always start on Kraken, so that we should expect a large number of orders in a given month on this exchange. Table A3 in the Internet Appendix presents detailed information on trading fees for all exchanges. Finally, we fix the margin fee required to maintain a short position on Kraken to 0.07%, which corresponds to the current opening fee plus the roll-over positions for 24 hours.

After accounting for both bid/ask spreads and trading fees, long/short returns for portfolio 7 are positive and statistically different from zero, and, as for our baseline portfolios, the Patton and Timmermann (2010) tests reject the null of flat or weakly decreasing pattern against the alternative of the strictly increasing pattern. Since measures of the historical bid/ask spreads are not available for all our pairs, in panels B and C, we use gross returns based on all available pairs, while bid-ask spreads are based on the subsample of available pairs. In panel D, we generate *synthetic* bid/ask spreads for all the pairs estimating the panel described in Equation (5). We find that, also in this case, the long/short returns for the last portfolio are positive and statistically significant.

Finally, panel E reports average returns net of trading fees and bid/ask spreads at the market depth of 10 BTC (approximately US$300,000 at the end of the sample), to account for sizeable trading positions. In this case, returns for all portfolios are large and negative. Therefore, the size of trades matters: once we account for market depth, returns become large and negative at orders larger than US$300,000, which correspond to approximately 6% of the daily median trading volume and is five times larger than the 10th percentile. Market depth introduces a constraint on the maximum trade size to obtain non-negative expected returns, which influences the likelihood that large investors would engage in this trade and the opportunity for investors to fully absorb bitcoin price differences.

3.3 Sharpe ratios and crypto shares

In Table 2, we presented the properties of seven portfolios sorted by bitcoin discounts for two strategies, that is the *cross* and *within* strategies. In our discussion, we highlighted the very large Sharpe ratios associated with these portfolios, even after accounting for bid/ask spreads. Specifically, we documented a daily Sharpe ratio of 26% for the long/short *cross* strategy, and of 17% for the long/short *within* strategy. These figures are large compared, for example, with the Sharpe ratio of the U.S. equity market over the same period (i.e., approximately 4%).

Because the typical investor does not have all of her wealth invested in these strategies, a more meaningful comparison for the risky proxy calculation is probably to consider an investor who holds a relatively small fraction of her portfolio in crypto assets, and the rest in traditional assets, for example the U.S. equity market. Figure 4 illustrates this comparison by reporting the daily Sharpe ratios of portfolios with a weight w that goes from 0% to 10% in the long/short crypto strategy, and with a weight $1 - w$ in the U.S. equity market portfolio. The figure illustrates a simple point: investing a small fraction of your aggregate portfolio in the long/short strategies would increase the portfolio Sharpe ratio only marginally. For example, for the *cross* strategy, a portfolio with a weight of 1% in crypto would be associated with a Sharpe ratio of 4.3%.

3.4 Alternative samples

Table 8 documents the average portfolio discounts and net *cross* and *within* returns for alternative samples. All samples end on May 25, 2021, while the starting dates differ as we will describe below.

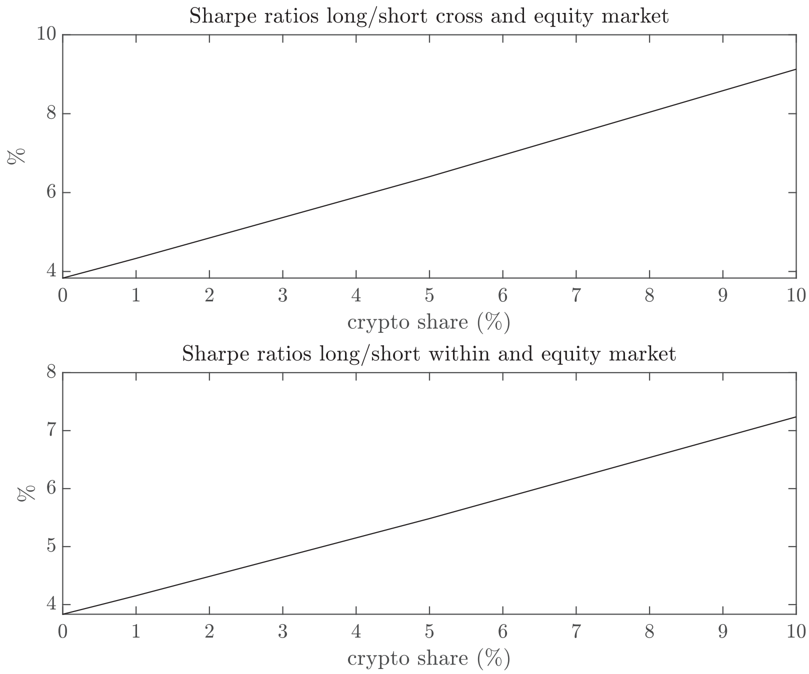

Figure 4
Sharpe ratios and crypto shares
This figure plots the Sharpe ratios associated with portfolios invested with a weight w that goes from 0% to 10% in the long/short crypto strategy, and with a weight $1 - w$ in the U.S. equity market portfolio. The top panel corresponds to the *cross* strategy and the bottom panel corresponds to the *within* strategy. Daily data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters. The sample period is May 26, 2015, to May 25, 2021.

Panel A, for convenience, summarizes the baseline results also reported in Table 2. Panel B considers a shorter sample for the same pairs; the sample starts on January 2, 2018, when crypto "came of age" and after the bitcoin frenzy of 2017. Also in this sample, *cross* net returns increase monotonically from the last to the first portfolio. The average long/short return is 46 basis points per day, statistically different from zero at conventional levels and very close to the value obtained in the longer sample. Similarly to the baseline sample, *within* portfolio net returns decrease from portfolio 1 to portfolio 7, but are negative for all portfolios.

Panel C considers a sample that includes a larger set of the fiat-to-bitcoin pairs available on the Cryptocompare website (https://cryptocompare.com).[10] Also in this sample, *cross* net returns are monotonically increasing from the last to the first portfolio. Returns are, on average, higher than in the

[10] The sample includes 146 pairs for 15 fiat-to-bitcoin pairs traded on 81 exchanges located in 27 countries around the world. The additional fiat currencies are Brazilian real, Chinese yuan, Hong Kong dollar, Korean won, Mexican peso, Russian ruble, Singapore dollar, Ukrainian hryvnia.

Table 8
Bitcoin portfolios: alternative samples

Portfolio	1	2	3	4	5	6	7	Long/short
				A. *Baseline sample*				
				Discounts				
Mean	−0.97	−0.28	−0.08	0.08	0.26	0.51	1.52	
SE	0.04	0.02	0.02	0.02	0.02	0.02	0.05	
				Cross net returns				
Mean	−0.23	0.15	0.26	0.35	0.46	0.62	1.10	**0.59**
SE	0.12	0.11	0.11	0.12	0.12	0.12	0.12	0.06
				Within net returns				
Mean	0.46	0.26	0.22	0.14	0.07	−0.07	−0.77	**−0.37**
SE	0.12	0.12	0.12	0.12	0.12	0.11	0.12	0.06
				B. *Baseline sample, since 2018*				
				Discounts				
Mean	−0.75	−0.18	−0.05	0.06	0.18	0.37	1.16	
SE	0.03	0.01	0.01	0.01	0.01	0.02	0.05	
				Cross net returns				
Mean	−0.47	−0.01	0.07	0.11	0.13	0.27	0.74	**0.46**
SE	0.17	0.17	0.16	0.17	0.16	0.16	0.18	0.05
				Within net returns				
Mean	−0.06	−0.04	−0.04	−0.10	−0.22	−0.29	−0.69	**−0.56**
SE	0.17	0.16	0.16	0.17	0.17	0.16	0.15	0.04
				C. *All fiat-to-bitcoin pairs*				
				Discounts				
Mean	−1.94	−0.39	−0.02	0.25	0.61	1.29	4.31	
SE	0.05	0.02	0.02	0.02	0.03	0.04	0.09	
				Cross net returns				
Mean	−0.97	0.10	0.35	0.47	0.71	1.16	3.94	**4.36**
SE	0.12	0.12	0.12	0.12	0.12	0.12	0.16	0.13
				Within net returns				
Mean	0.80	0.34	0.26	0.09	−0.06	−0.36	−0.72	**−0.04**
SE	0.12	0.12	0.12	0.12	0.12	0.11	0.15	0.10
	D. *All crypto-to-bitcoin pairs*							
				Discounts				
Mean	−2.95	−0.43	−0.14	−0.02	0.08	0.26	1.91	
SE	0.11	0.02	0.00	0.00	0.00	0.01	0.05	
				Cross gross returns				
Mean	−0.28	−0.02	0.26	0.62	0.52	0.17	0.71	**0.99**
SE	0.32	0.15	0.19	0.33	0.27	0.18	0.21	0.13
				Within gross returns				
Mean	3.10	0.42	0.43	0.79	0.48	−0.09	−0.97	**4.07**
SE	0.40	0.16	0.21	0.42	0.33	0.18	0.24	0.11
				E. *All crypto-to-fiat pairs*				
				Discounts				
Mean	−2.03	−0.52	−0.20	0.03	0.32	0.81	2.94	
SE	0.05	0.02	0.02	0.01	0.02	0.03	0.07	
				Cross gross returns				
Mean	−0.00	0.42	0.46	0.55	0.69	1.08	2.13	**2.13**
SE	0.13	0.13	0.13	0.13	0.14	0.13	0.13	0.13
				Within gross returns				
Mean	2.13	0.93	0.65	0.50	0.37	0.26	−0.71	**2.84**
SE	0.15	0.15	0.14	0.15	0.13	0.13	0.14	0.11

This table reports, for each portfolio *j* and different samples, the means and bootstrap standard errors of the average discounts and *cross* and *within* returns for portfolios sorted by bitcoin discounts. All samples end on May 25, 2021. The long/short returns are in bold. Panel A corresponds to the baseline sample and a period starting May 26, 2015. Panel B considers the same pairs over a shorter period starting January 2, 2018. Panel C considers a sample that includes a larger set of the fiat-to-bitcoin pairs available on the Cryptocompare website (https://cryptocompare.com) for a period starting May 26, 2015. Panel D and E consider, respectively, a sample containing 411 crypto-to-bitcoin pairs and 274 crypto-to-fiat pairs (excluding bitcoin) for a period starting March 31, 2016. The crypto pairs in panels D and E are ADA, BCH, DOGE, EOS, ETC, ETH, LTC, XLM, XMR, and XRP. The fiat pairs in panel E are AUD, CAD, CHF, EUR, GBP, JPY, PLN, and USD. All returns, with the exception of those of Panel D and E, are net of bid/ask spreads. All returns are in units of dollars per bitcoin except those reported in panel D which are in units of ETH per bitcoin and panel E which are in units of dollars per ETH. Daily data come from the Cryptocompare website (https://cryptocompare.com), Bitcoinity, and Thomson Reuters.

baseline sample and the mean long/short return is equal to 436 basis points per day and statistically different from zero. However, these large returns are most likely not attainable. In fact, this sample includes pairs from countries with restrictions on capital flows, limiting investors' ability to transfer money in, and out of, some of the exchanges. Although some of the capital control measures are likely to bite more retail than large investors (Baba and Kokenyne, 2011), they are likely to make the *cross* strategy difficult to implement. Further, according to various quality indicators some of the exchanges are less reliable and some of the pairs are associated with lower trading volume. Similarly to the baseline sample, *within* returns decline monotonically from the first to the last portfolio, and the long/short return is negative and not statistically different from zero after accounting for bid/ask spreads.

Panel D considers a sample containing several crypto-to-bitcoin pairs for a period starting on March 31, 2016, when data for a number of pairs sufficient to build portfolios are available. Specifically, we include 411 pairs traded on 87 exchanges for 10 of the most-traded cryptocurrencies against bitcoin.[11] For each crypto-to-bitcoin pair, we select from the Cryptocompare website (https://cryptocompare.com) the exchange-pairs corresponding to the top 20 in terms of trading volume as of May 2021, and compute prices and returns measured in units of ETH per bitcoin, and discounts with respect to the ethereum-to-bitcoin pair on Kraken. We focus on gross returns because of the unavailability of the historical bid/ask spreads for most of the pairs. Even though transferring cryptocurrencies, as opposed to fiat currencies, should be less restrictive from the perspective of domestic regulations of international flows, we document a large cross-section of discounts, from −2.95% on the first portfolio to 1.91% on the last portfolio. Also for this sample, we find evidence of economically large increasing *cross* returns and decreasing *within* returns. The mean return on the long/short strategies is positive, statistically different from zero, and larger than for the bitcoin pairs. This is not surprising as these returns are before transaction costs, which are likely to be larger for crypto pairs different from bitcoin, because these pairs tend to be less liquid. However, because of the unavailability of the historical bid/ask spreads for most of the pairs, we could not test this conjecture.

Finally, panel E considers a sample containing 274 crypto-to-fiat pairs, excluding bitcoin, for a period starting on March 31, 2016, when data for a number of pairs sufficient to build portfolios are available. Specifically, we consider the same cryptocurrencies included in the sample from panel D and the following eight fiat currencies: Australian dollar, Canadian dollar, Swiss franc, Euro, British pound, Japanese yen, Polish zlot, and U.S. dollar. These pairs are traded on 29 exchanges and we compute prices and returns

[11] The 10 cryptocurrencies are cardano (ADA), bitcoin cash (BCH), dogecoin (DOGE), EOS, ethereum cash (ETC), ethereum (ETH), litecoin (LTH), stellar (XLM), monero (XMR), and ripple (XRP).

Table 9
Execution risks

	Cross portfolios							*Within* portfolios						
Portfolio	1	2	3	4	5	6	7	1	2	3	4	5	6	7
	A. *Baseline gross returns*													
Mean	0.14	0.39	0.45	0.55	0.66	0.86	1.53	1.15	0.68	0.53	0.47	0.40	0.35	0.03
SE	0.12	0.12	0.12	0.12	0.11	0.12	0.11	0.13	0.12	0.12	0.12	0.12	0.12	0.11
	B. *Sell at zero price when exchange shutdowns*													
Mean	−0.73	0.26	0.29	0.42	0.46	0.71	1.03	0.26	0.55	0.37	0.35	0.20	0.20	−0.46
SE	0.18	0.13	0.14	0.13	0.13	0.13	0.16	0.19	0.13	0.14	0.13	0.14	0.13	0.15
	C. *Sell at low price of the day*													
Mean	−3.30	−2.88	−2.74	−2.67	−2.55	−2.33	−1.69	−2.35	−2.61	−2.66	−2.74	−2.80	−2.81	−3.13
SE	0.11	0.11	0.11	0.11	0.11	0.10	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
	D. *Sell at mean low/high price of the day*													
Mean	−1.58	−1.25	−1.15	−1.06	−0.95	−0.73	−0.08	−0.60	−0.96	−1.06	−1.14	−1.20	−1.23	−1.55
SE	0.11	0.10	0.10	0.11	0.10	0.11	0.11	0.11	0.10	0.11	0.10	0.10	0.11	0.11

This table reports, for each portfolio j, the mean *cross* and *within* returns, and corresponding standard errors by bootstrap, for the seven portfolios sorted by bitcoin discounts. Panel A reports the baseline gross returns. In panel B, we assume that investors always close their trades at a price of zero if a pair available at time t then drops out of the sample at $t+1$. In panel C, we assume that investors close their trades at $t+1$ always at the lowest price of the day for a given exchange-currency pair. In panel D, we assume that investors close their trades at $t+1$ always at the mean between the closing and the lowest price of the day. All returns are before transaction costs. Daily data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters. The sample period is May 26, 2015, to May 25, 2021.

measured in units of dollar per ETH and discounts with respect to the ethereum-to-dollar pair on Kraken. Also in this sample, we find a large cross-section of discounts, from −2.03% on the first portfolio to 2.94% on the last portfolio, which is matched by an increasing cross-section of *cross* returns and a declining cross-section of *within* returns. The mean return on the long/short strategies is positive, large and statistically different from zero, although we note that returns are before transaction costs because of the unavailability of the historical bid/ask spreads for most of the pairs.

3.5 Execution risk

Bitcoin investors are exposed to different forms of execution risks. While all investors face the risk that they cannot execute a transaction within the range of market prices observed before sending their orders, *cross* investors face additional risks related to the transfer of balances across exchanges.

Table 9 documents the effect of different forms of execution risk. In our baseline analysis, when a pair is available at time t, but not at time $t+1$, we assume that investors close their trade at the median closing price across all pairs. We refer to this situation as an "exchange shutdown." These events can be temporary, for example because of a software malfunctioning or denial-of-service attack, or permanent in case of bankruptcy. While panel A reports the baseline *cross* and *within* portfolio returns, and panel B documents average returns under the more conservative assumption that investors must sell their balance at a zero price (i.e., for a −100% return). In this case, average returns are lower. For *cross* portfolios, the average return on portfolio 7 remains highly significant. In contrast, for *within* portfolios, the average return on portfolio 1 becomes not statistically different from zero. Table A6 in Section D of the Internet Appendix reports estimates of the returns for investors who had their balances *stuck* in an exchange because of a long shutdown. Under the assumption that investors sell their balance at the price of the day in which the exchange finally reopens, we show that returns are, on average, slightly negative.[12]

The definition of excess returns from Equation (3) relies on the assumption of near-instant speed of execution at daily closing prices. Completing a trade requires the time to transfer bitcoins across exchanges and to execute a trade within the exchange. It is difficult to exactly quantify these amounts of time, as they both depend on the *type* of investor (i.e., retail or hedge fund) and the state of the network. The time required by the bitcoin blockchain to transfer bitcoins across exchange wallets depends on the congestion of the network and has recently ranged anywhere between 10 minutes to 24 hours. On the other hand, trade execution within an exchange is much faster, with only 3.95% of trades taking longer than one second to be executed for the largest exchanges (Krückeberg and Scholz (2020)), but with delays for some of the exchanges (e.g., Bitfinex's average order execution delay is 156 milliseconds). Panels C and D report returns under different scenarios. Panel C assumes that investors always sell at the lowest price of the day for a given pair. In this case, we obtain a cross-section of both *cross* and *within* returns, but the average returns are large and negative for all portfolios, dropping by an average of 325 basis points. Returns reported in panel D are based on the assumption that investors always sell at the average price between the high and the low price of the day for a given pair. In this case, all portfolio returns are negative and the average return drops by 162 basis points. In sum, our results indicate that bitcoin execution risk can significantly lower the returns to investors and contributes to explain bitcoin price differences across exchanges and currency pairs. The effects of execution risk are likely to play a smaller role in the future as the technological infrastructure of exchanges evolves to reduce these risks.[13]

[12] Moore and Christin (2013) find that, by early 2013, 45% of bitcoin exchanges had closed, and many of the remaining markets were subject to frequent outages and security breaches, while Vasek and Moore (2015) document several denial-of-service attacks against cryptocurrency exchanges. In our sample, on a given day, approximately 14% of the pairs are not available (see Figure A11 in the Internet Appendix). The numbers reported in Table 6 correspond to the fraction of pairs active at time t, but not at time $t+1$. Finally, Table A5 in the Internet Appendix lists critical events for the largest cryptocurrency exchanges.

[13] In the Internet Appendix, we present additional evidence about execution risk. Section F.XI shows that pairs in the corner portfolios are less liquid, as measured by the Amihud (2002) illiquidity measure. For the spot currency market, Ranaldo and Santucci de Magistris (2019) show that violations of the triangular arbitrage parity are more likely for less liquid pairs. Section G shows that corner portfolios are also associated with higher idiosyncratic risk, which could motivate an alternative explanation for the documented cross-section of returns based on costly arbitrage and idiosyncratic risk (Pontiff, 1996).

Table 10
Bitcoin portfolios: U.S. investor (weekly frequency)

Portfolio	1	2	3	4	5	6	7	Long/short
				A. *Discounts*				
Mean	−1.00	−0.26	−0.04	0.12	0.31	0.57	1.60	
SD	1.63	0.65	0.54	0.57	0.79	1.02	1.71	
				B. Cross *returns*				**7-1**
				Gross returns				
Mean	2.14	2.22	2.45	2.46	2.59	2.77	3.22	1.08
SD	11.04	10.73	11.43	11.00	10.98	11.00	10.95	1.80
SE	0.62	0.61	0.67	0.65	0.63	0.61	0.62	0.10
SR	0.19	0.21	0.21	0.22	0.24	0.25	0.29	0.60
				Returns net of bid/ask				
Mean	1.77	1.99	2.26	2.28	2.39	2.54	2.80	0.27
SD	11.10	10.72	11.39	11.01	11.01	11.02	11.02	1.95
SE	0.63	0.62	0.64	0.61	0.64	0.63	0.62	0.11
SR	0.16	0.19	0.20	0.21	0.22	0.23	0.25	0.14
				C. Within *returns*				**1-7**
				Gross returns				
Mean	3.19	2.49	2.49	2.34	2.27	2.19	1.62	1.56
SD	11.12	10.76	11.40	10.96	10.91	10.90	10.75	2.60
SE	0.65	0.62	0.63	0.62	0.63	0.61	0.63	0.15
SR	0.29	0.23	0.22	0.21	0.21	0.20	0.15	0.60
				Returns net of bid/ask				
Mean	2.50	2.07	2.16	2.04	1.91	1.79	0.83	0.08
SD	11.16	10.81	11.38	10.97	10.95	10.93	10.87	2.34
SE	0.65	0.62	0.66	0.63	0.62	0.64	0.61	0.12
SR	0.22	0.19	0.19	0.19	0.17	0.16	0.08	0.04

This table reports, for each portfolio, the mean and standard deviation for bitcoin discounts; the excess *cross* returns, and the high-minus-low returns from a zero-cost strategy 7-1; and the excess *within* returns, and the high-minus-low returns from a zero-cost strategy 1-7. For returns, we also report standard errors by bootstrap and gross and net returns. We divide each year into 52 weeks. The first week of the year consists of the first 7 days of the year. The first 51 weeks of the year consist of 7 days each and the last week of the year consists of the last 8 days of the year. For both the *cross* and *within* returns, the holding period is equal to 5 days, because we exclude nonbusiness days, like Saturdays and Sundays. Transaction costs include bid-ask spreads, but do not include trading, margin, and exchange fees. Portfolios are constructed by sorting assets into seven groups at time t by their discounts. The first portfolio contains assets with the lowest negative discounts. The last portfolio contains assets with the highest positive discounts. Weekly data come from the Cryptocompare website (https://cryptocompare.com) and Thomson Reuters. The sample period is May 27, 2015, to May 20, 2021.

3.6 Weekly rebalancing

In our baseline analysis, we consider a period of 1 day and form daily bitcoin portfolios. One reason of concern is the implementability of the *cross* and *within* strategies at the daily frequency. For example, the time to execute a trade on a given exchange, and the convertibility in fiat currencies and the transfer of balances across different exchanges, might put a constraint on the rebalancing frequency. On the other hand, a slower frequency of rebalancing might reduce transaction costs (i.e., bid/ask spreads and trading fees), thereby substantially reducing daily returns. In this section, we show that our results also hold at a lower frequency of trading.

We leave the details about the construction of the weekly portfolios to Section F.VI in the Internet Appendix and present here the properties of the weekly portfolios (see Table 10). Panel A reports the average bitcoin discounts. The mean discounts increase monotonically from −100 basis points for the first portfolio to 160 basis points for the last portfolio. We start with the description of *cross* portfolio returns (panel B). Similarly to the sample at the daily frequency, also at the weekly frequency excess returns increase monotonically across portfolios: gross returns increase from approximately 214 basis points to 322 basis points *per week*. The long/short 7-1 average return, before transaction costs, is equal to 108 basis points. Accounting for the bid/ask spread reduces the average long/short return by approximately 81 basis points. The net average long/short return is equal to 27 basis point, and is statistically different from zero (the standard error is equal to 11 basis points). To facilitate the comparison with the portfolios at daily frequency, we recall that the average net long/short return at the daily frequency is equal to 59 basis points *per day* and, thus, one order of magnitude larger than the average net long/short return at the weekly frequency (i.e., $27/5 = 5.4$ basis points *per day*, where 5 is the number of days in the holding period). Panel C considers *within* returns. Also, in this case, we qualitatively replicate the results of the portfolios at daily frequency. Specifically, we obtain a monotonically decreasing cross-section of portfolio gross and net returns. Note that the average portfolio net returns are positive for all portfolios, while the average net long/short *within* return is equal to 8 basis points *per week*, but not statistically different from zero.

3.7 Out-of-sample

We investigate whether our results hold out-of-sample by constructing two nonoverlapping random selected groups of approximately the same size from the universe of pairs of the baseline sample. First, we form portfolios sorted by bitcoin discounts for each of the two groups. Because of the lower number of pairs per group, we now form only five portfolios. We obtain a monotonically increasing cross-section of *cross* net returns in both samples (see Table A12 in Section F of the Internet Appendix). Second, we construct the $Carry_{Btc}$ factor from portfolio returns of the *first group*, and repeat the asset pricing exercise using as test assets the portfolios of the *second group*. Note that, as the portfolios are formed using two nonoverlapping sets of pairs, $Carry_{Btc}$ is constructed from pairs that are different with respect to those contained in the portfolios used as test assets. Specifically, $Carry_{Btc}$ is now the return from a zero-cost strategy that goes long in portfolio 5 and short in portfolio 1 from the *first* sample. We find that the estimate for the market price of the $Carry_{Btc}$ factor is significant and similar to the one we obtain in our baseline asset pricing estimation. The full asset pricing results are reported in Table A13 in Section F of the Internet Appendix.

4. Conclusions

Common explanations of the large bitcoin price differences across exchanges and currency pairs are limits to arbitrage and market efficiency, as argued in the influential paper by Makarov and Schoar (2019). According to this view, cryptocurrencies are not a "normal" asset class. In this paper, we propose a more balanced view and show that while there are some arbitrage-like opportunities, they are not riskless.

We propose a novel risk-based explanation of bitcoin price differences and carefully account for all the transaction costs and limitations to trade. Bitcoin prices for more "expensive" pairs depreciate more in bad times for cryptocurrency investors, when aggregate liquidity is lower and more uncertain, and investor sentiment about bitcoin is lower. Available returns compensate investors for taking on more aggregate risk.

We identify common risk factors in the data by building portfolios sorted on bitcoin past price deviations. By forming portfolios we can focus on the common components in bitcoin returns, accommodate variations in the number of exchanges and currencies pairs, and average out idiosyncratic risks. A two-factor model explains a large fraction of the cross-sectional variation in portfolio returns. Therefore, our results support the conclusion that the documented cross-section of returns represents compensation for risk, and is not just a measure of the inefficiency of cryptocurrency markets.

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